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Multimodal Robotic Health in Future Factories Through IIot, Data Analytics, and Virtual Commissioning

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DEDICATION

To my parents who struggled and sacrificed so that I could achieve my dreams.

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ABSTRACT

The manufacturing sector is continuously reinventing itself by embracing opportunities offered by the industrial internet of things and big data, among other advances. Modern manufacturing platforms are defined by the quest for ever increasing automation along all aspects of the production cycle. Furthermore, in the next decades, research and industry are expected to develop a large variety of autonomous robots for a large variety of tasks and environments enabling future factories. This continuing pressure towards automation dictates that emergent technologies are leveraged in a manner that suits this purpose. These challenges can be addressed through the advanced methods such as [1] large-scale simulation, [2] system health monitoring sensors and [3] advanced computational technologies to establish a life-like digital manufacturing platform and capture, represent, predict, and control the dynamics of a live manufacturing cell in a future factory.

Autonomy is a desirable quality for robots in manufacturing, particularly when the robot needs to act in real-world environments together with other agents, and when the environment changes in unpredictable or uncertain way. This dissertation research will focus on experimentally collecting sensor signals from force sensors, motor voltages, robot monitors and thermal cameras to

connect to such digital twin systems so that more accurate real-time plant descriptions can be collected and shared between stakeholders. Creating a future factory based on an Industrial Internet-of-Things (IIoT) platform, data-driven science and engineering solutions will help accelerating Smart Manufacturing Innovation. Besides, this study will examine the ways of sharing knowledge between robots, and between different subsystems of a single robot, and implement concepts for communicating knowledge that are machine logical and reliable. My work will focus on applying the proposed methodology on more diverse manufacturing tasks and materials flows, including collaboratively assembly jobs, visual inspection, and continuous movement tasks. These tasks will require higher-dimensional information such as, analog plant signals, and machine vision feedback to be fed into and train the digital twin.

PREFACE

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All the experimental work was conducted at the neXt Future Factories Robotic Cell located in the McNAIR Aerospace Center at the University of South Carolina-Columbia, SC.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AFP .... Air Force Base

AI .... Artificial Intelligence

ANN .... Artificial Neural Network

API .... Application Programming Interface

AR .... Augmented Reality

ARL .... Average Run Length

BDA .... Big Data Analysis

BPNN .... Back Propagation Neural Network

CAD .... Computer Aided Design

CAE .... Computer Aided Engineering

CAM .... Computer Aided Manufacturing

CAPP .... Computer Aided Process Planning

CAX .... Computer Aided Technologies

CBDT .... Cloud Based Digital Twins

CBM .... Condition Based Maintenance

CNC ....Computer Numerical Control

CPCM ....Cyber Physical Cloud Manufacturing

CPS .... Cyber-Physical System

CUSUM..Cumulative Sum Control Chart

DDS ....Dynamic Data Systems

DoD .... Department of Defense

DT ....Digital Transformation

EIT .... Enterprise Information Technology

EPQ .... Economic production Quantity

ETSI..................................... European Telecommunications Standards Institute

FLIR...Forward-Looking Infrared

HMI .... Human-Machine Interface

IAAS ....Infrastructure as a Service

ICT ....Information and Communication Technology

IEEE..Institute of Electrical and Electronics Engineers

IETF.. Internet Engineering Task Force

IIOT..Industrial Internet of Things

INCOSE...International Council on Systems Engineering

IOT..Internet of Things

KPI .... Key Performance Indicator

M2M.. Machine to Machine

MBE ....Model Based Engineering

MBSE ....Model Based System Engineering

MHI ....Materials Handling Institute

MR ....Mixed Reality

NIST ....National Institute of Standards and Technology

OCR...Optical Character Recognition

OPC ....Open Platform Communications

PAAS..Platform as a Service

PLC ....Programmable Logic Controller

PLM ....Product Lifecycle Management

QR .... Quick Response

R-CNN.. Region-Based Convolutional Neural Networks

RIA ....Robot Institute of America

RQ ....Research Question

SAAS..Software as a Service

SOA ....Service Oriented Architecture

SPC...Statistical Process Control

SVM .... Support Vector Machine

TCP..Transmission Control Protocol

UA ....Unified Architecture

VR .... Virtual Reality

CHAPTER 1

INTRODUCTION

1.1 PREAMBLE

Industry 4.0 has become a synonym for a vision of future product creation and production engineering environments in which networks of horizontally and vertically integrated smart design and manufacturing systems will be the norm. With the Internet of Things (IoT) and its Cyber-Physical Systems as a backbone, game-changing new ways of product design and manufacturing in a hyper-connected globalized world are emerging. In addition, a new and rapidly growing industrial service-sector focusing on Product-Service-Systems has begun to form. Some of the challenges in realizing the overall vison of Industry 4.0 concern the integration, management, control and communication of cyber-physical production engineering systems, the integration of state-of-the-art technology within the legacy systems, data security and broader cyber-security aspects, as well as national and international public policy issues (Figure 1.1, page 8). Lastly, given the profound impact of this so-called 4th Industrial Revolution on society, the changing landscape of tomorrow's job market and hence the training and education of the next generation workforce need to be addressed as well.

Industries and engineering applications around the world are embracing the concept of Digital Industrial Transformation and Industry 4.0 to attain greater levels of business, asset, and product life management (PLM). This process allows for machines, systems, and users to be interconnected, which supports faster decision-making and less downtime.

The future of manufacturing is reinventing itself by embracing the opportunities offered by digital transformation, industrial internet, cognitive automation, and artificial intelligence. Cyber-physical systems (CPSs) are looking to pursue the potential convergence of cyber architectures, physical manufacturing processes, and control intelligence. In this section, the authors introduce a novel cyber-physical infrastructure enabled by these technological elements, followed by proposing to utilize a machine vision system to aid general manufacturing event understandings.

This work demonstrates a cyber-physical system of a five-robot assembly line. Collaborative robots from Yaskawa Motoman are controlled by a safety-enabled Siemens S7-1516F PLC system. Industrial sensors and vision systems are embedded as smart devices to monitor the process indicators and device health states during machine operations. The cyber infrastructure is constructed based on a Siemens virtual commissioning solution, Process Simulate, which accommodates a high-fidelity simulation-based digital twin for the physical assembly line. Industrial implementations of robotic production lines are widely adopted to automate specific manual processes to further meet the manufacturing requirements in sterility, precision, or workload capacity. However, the needs to adaptively change the robot action sequences in dynamic work cells have drawn the attention of manufacturing practitioners, as expected and unexpected incidents can and do occur during the processes. Such adaptivity requires reliable, precise, and prompt manufacturing event-understanding by machines. Hence, this work proposes to develop a deployable system connecting the cyber and physical world. The synchronized results from multiple sources are expected to aid the machine event-understandings along with the signals from conventional industrial sensors. One goal of this project is to use a sensor array to create real time feel and control of the robotic cell. The system will be designed to either alert human or AI monitors of the manufacturing cell of any inefficiencies, allowing them to analyze the system to find and remedy the source of error. The other goal for this project will be to integrate the data collected by the sensors into the Digital Twin of the robotic cell.

This integration of real-world data and computer simulations has a widespread current and future application in prognostics and health management. Furthermore, it could be very useful in terms of accurately modeling and predicting damage to systems, which would enhance safety. In addition, used technologies are a viable alternative to current shortcomings of robotic resource management and sustainment.

The objective of this work is to develop an industrial system for smart manufacturing control system in both virtual and physical spaces. Based on current large-scale simulation, sensor and computation technologies, the method to pursue this is to establish a life-like digital manufacturing platform and capture, represent and predict the dynamics of a live manufacturing cell.

1.2 HISTORICAL PERSPECTIVE

Historians have reported a succession of Industrial revolutions starting in the 18th century. These industrial events were driven by new technologies and systematically resulted in wholesale disruptions and transformations in industrial processes, manufacturing methodologies, business models and the organization of capital and labor. They are usually frames-of-reference for the intersection of events and emergent technologies that often led to marked shifts in productivity, Industry and society. These shifts have often resulted not only in global reorganization of the means of production but also in remarkable changes to the socio-political, cultural and economic fortunes of nations. Industry watchers have identified four different industrial revolutions, though there are early contemplations about a fifth industrial revolution.

The 1st Industrial revolution (Industry 1.0) occurred within the 18th century, spanning the period 1760 and 1840, circa. It welcomed mechanized production using coal resulting in the transition from muscle power to mechanical power. It was triggered by the invention of the stream engine, hydropower and the emergence of the railroad construction industry. The major contribution of this era was improved efficiency. The second industrial revolution (Industry 2.0) started in the late 19th century but continued through the early 20th century. It enabled mass production after the arrival of electric power and the advent of the assembly line enabling the mass production of goods and kick-starting the era of automation. The third Industrial revolution (otherwise known as the computer or digital revolution) began in the middle of the 20th century (1960, circa). It made automated production possible using machine control and robots. Electronics and information technology were key technologies of this era. Other key elements of this period include the rise of computer networks, the emergence of the Internet and the arrival of robots. Last but not least, the fourth industrial revolution would involve the representation of physical objects in highly interactive virtual information networks, where the boundaries between the physical and virtual worlds continue to blur. This era spurred a jump from a reliance on the client-server model to ubiquitous mobility that has catalyzed the growth smart things. Other remarkable elements of this era include the growth of exponential technologies like artificial intelligence (AI), Blockchain, Big data and analytics, augmented and virtual reality (AR, VR), robotics etc. Industry 4.0 is a construct of the fourth industrial revolution that seeks to bringing together the various conceptual elements that will frame the transformation that is expected to occur due to the collision of these technologies and events. The Future Factory would be one of many outcomes of this construct.

1.2.1 The rise of computers

The embrace of information technology began in the 1950's. Researchers from that period through the 1980's often stated that an old era was ending and a new era was beginning, and that this was due to computers [38][55][75]. Computer use in manufacturing began with numerical control (NC)– the feeding of step-by-step, pre-programmed instructions to a machine that translated the instructions into movements to perform subtractive manufacturing, usually milling or turning. NC was first proposed in the 1940's by John Parsons who worked in aircraft manufacturing. He proposed the idea to Wright-Patterson AFB, who then commissioned development from MIT. When the first commercial machines were available in 1955, they were controlled by paper or magnetic tape bearing the instructions. The tapes began to be replaced in the late 1960's by central computer control. Central control expanded NC to allow multiple machine control and closed-loop control where the machines were able to report status to the controlling computer [38].

The development of simulation programs to design and predict manufacturing processes began in the late 1970's [49][75][83]. Programs were designed to evaluate systems before implementation, monitor systems in operation, and collect data of the results. Models of dynamic changes during operation, such as tool wear, were developed to better simulate operations. One author noted that the industrial age is mature and "approaching seniority," arguing that computer control and artificial intelligence are needed to compete in the new global marketplace [56]. Closed-loop numerical control combined with computer simulation has led to smart manufacturing and the beginnings of digital twins and virtual commissioning.

1.3 DOCUMENT ORGANIZATION

In this work, a novel approach is proposed to establish continuous interfaces with a virtual environment accommodated by industrial computer-aided applications to overcome production bottlenecks towards data-driven digital manufacturing systems. The proposed method to pursue is based on current virtual commissioning applications is to employ large-scale simulations, prompt system indicators, and computation technologies to establish a life-like digital manufacturing platform, where dynamics of live manufacturing cells can be captured, represented, predicted, and controlled.

The document is organized as follow: Chapter 2 provides a review of existing research topics on digital transformation in production systems. Chapter 3 introduces the system environment; the virtual cell and its capability to simulate manufacturing problems. It will also present the interfaces between the systems and demonstrates near Realtime communications using the implemented interfaces. Sections 3.1 and 3.2 present some primary training results with a specific case study on gripper health monitoring and robot health mounting and deterioration. The last Section 7 concludes the main contributions of this work and proposes future research directions.

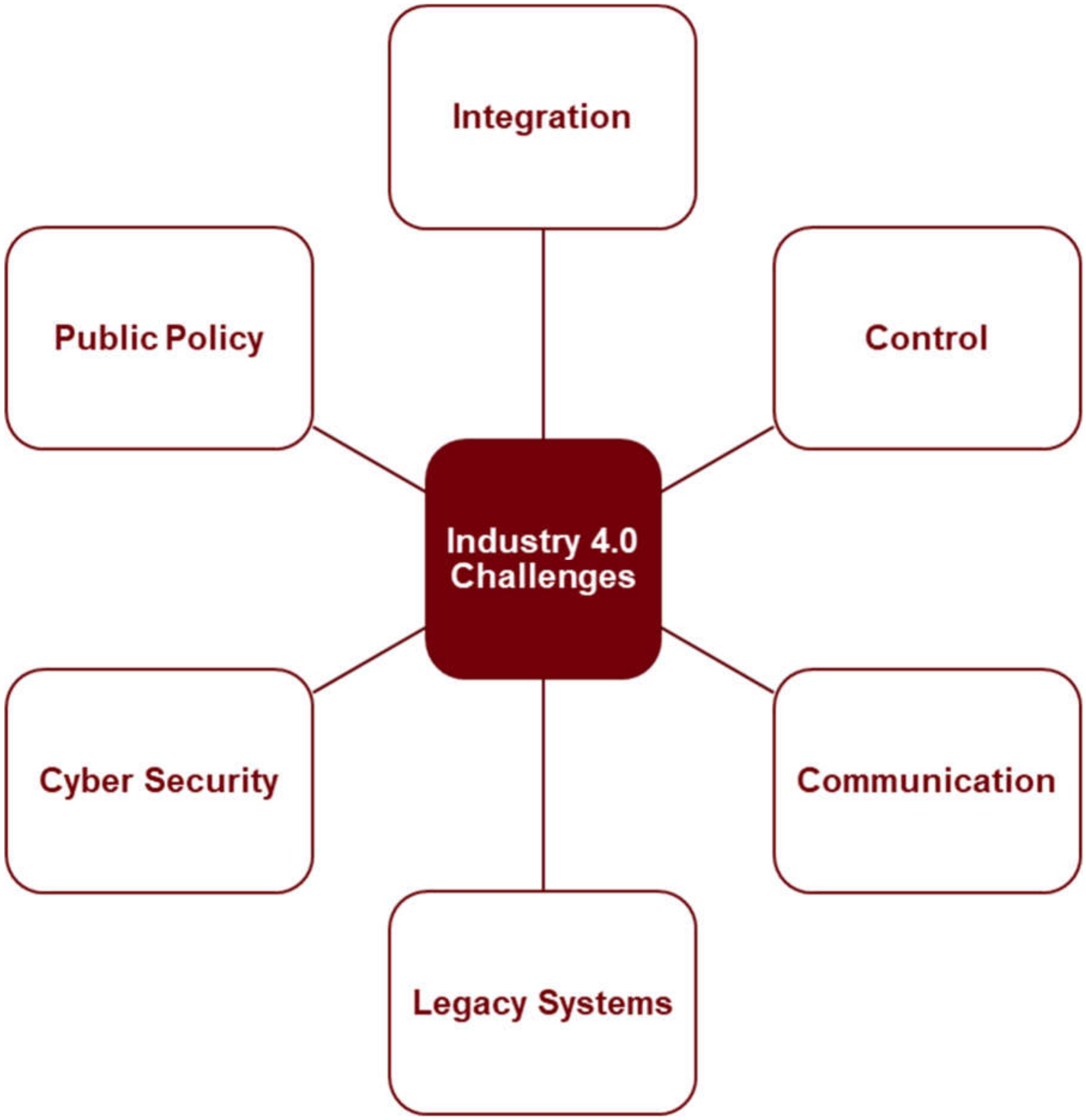

Figure 1.1: The Challenges of Implementing Industry 4.0

CHAPTER 2

LITERATURE REVIEW

This literature review will be divided into three main sections, with the first section focusing on a background literature on industry 4.0 and digital transformation putting things in perspective. It is more than just a chronology but focuses more on recent usage and difference implantations of the digital transformation philosophy. The next two sections will focus on more relevant question related to the specific topic of my dissertation: robot autonomy, and robot failure.

2.1 LITERATURE ON INDUSTRY 4.0 AND DIGITAL TRANSFORMATION

Industries and engineering applications around the world are embracing the concept of Digital Industrial Transformation and Industry 4.0 to attain greater levels of business, asset, and product life management (PLM). This process allows for machines, systems, and users to be interconnected, which supports faster decision-making and less downtime.

This literature will look at the state of digital transformation in the last decade using a systematic literature review approach. This method will help characterize digital transformation and its employment in industry. This chapter will also provide evidence of benefits and challenges encountered while implementing digital transformation methods. A systematic literature review has commonly been recognized as a more thorough, effective, repeatable, and less subjective form of literature review that leads to evidence-based conclusions. In this framework, the term "evidence" is accepted as the synthesis of scientific studies and papers with preeminent substance on the specific topic of digital transformation, defined by the following focused research questions:

RQ1. What is digital transformation? How is it implemented in industry?

RQ2. What are the key technology drivers of digital transformation in industry?

RQ3. What empirical evidence is there concerning the benefits and impact of digital transformation?

RQ4. What empirical evidence is there concerning challenges and how to overcome them?

RQ5. What role does culture play in digital transformation?

The purpose of this chapter is to review the prominence of digital transformation in the last decade. In section two, we describe the methodology used to develop the systematic literature review. In section three, we will be present and interpret the findings and evidence to the proposed research questions. And finally, section four will include the concluding remarks, limitations, and recommendations.

2.1.1 Methodology of Systematic Review

The systematic review fulfills the requirement for scholars to review and summarize all obtainable evidence and data about some phenomenon ("Digital Transformation") in a comprehensive and objective approach. Implementing a systematic review consist of three distinct stages: (a) planning; (b) conducting the review; and (c) reporting the review [54]. This systematic literature review will be structured following guidelines and recommendations recommended by Kitchenham et al. (2004) [54], and Moher et al. (2009) [80].

The main step in the planning stage is the development of a review protocol which specifies all methods needed to undertake the review. The main advantage of building such protocols is to reduce the possibility of scholar subjectivity and favoritism.

2.1.1.1 Formulation of research questions

The formulation of the right research questions is a key step in developing the review protocol. We sought to cover all aspects of our research with the questions RQ1 – RQ5 listed above. The first research question (RQ1) is a wide-ranging question that will help define digital transformation and its application in industrial settings. The second question (RQ2) will help us recognize the key technological drivers of digital transformation in industry, (3) its benefits and impact, (4) its challenges, and (5) the role of culture in its advancement. The aim of this study is to answer these research questions.

2.1.1.2 Search and Assessment Strategies

Three electronic databases and research engines (Web of Science, Science Direct, and Google Scholar) were used to conduct the search and identify qualified studies. The search was limited to data published in the English language. The searches were conducted using synonyms or alternative expressions and combinations of these search terms: "digital transformation", "digital thread", "industry 4.0", "implementation", "key drivers", "benefits", "impact", "challenges", and "cultural adjustment". The combinations were created using Boolean operators (AND and OR). Reference lists of qualified studies were examined for other relevant citations.

After collecting prospective studies through the search process, a primary selection of articles based on titles and abstracts was conducted. Irrelevant articles were disregarded, and a deeper read of the selected ones was concluded. After reading and evaluating the nominated articles, another set of irrelevant papers was omitted, leaving a total of 85 articles to analyze. The next step was to conduct the review and present the results.

2.1.2 Findings and Presentation

A total of 85 papers were considered significant for this systematic literature review. Table 2.1 (page 46) shows the distribution of articles among various journals The International Journal of Production Research has the largest share of relevant articles. Figure 2.1 (page 47) depicts the distribution of articles by time of publication. Twenty-two articles (40%) were published in the years 2016 and 2017.

The data extracted from these articles is represented and interpreted below in the form of answers for our research questions.

2.1.2.1 RQ1. What is digital transformation? How is it implemented in industry?

The notion of digital transformation first started appearing in literature around 1968 in the fields of nuclear spectroscopy [121], and computer analysis of microscopic images [78]. However, this concept has evolved since then. Digital transformation is the integration and use of digital technologies into business and industrial processes to enable major improvements [30][69], fundamentally altering traditional ways of doing business and manufacturing by redefining capabilities, processes and relationships [71] It is concerned with the changes digital technologies can bring about in a company's business model, which result in changed products or organizational structures or in the automation of processes [40]. DT is realigning technologies and new business models to more effectively engage digital customers at every touchpoint in the customer experience life cycle [111]. Research on successful digital transformation is currently limited to identifying trends that show improved capabilities, and to the growing accessibility of electronic data to enrich products, services and customer relationships [113].

Industry 4.0, the implementation of digital transformation in industry, is the vision of a highly integrated smart factory, in which discrete products are mass produced sustainably to fulfil consumer demand in global competition [133]. The technological building blocks that are considered indispensable for Industry 4.0 are cyber-physical systems (CPS) and the internet of things (IoT) [13][41][67]. Industry 4.0, or smart manufacturing, primarily focuses on the end-to-end digitization and the integration of digital industrial ecosystems by seeking completely integrated solutions [136], and is characterized by connectivity, automation, digitalization and decentralization [41]. Most prominently, Germany has legislated and enacted its "Industrie 4.0" program, which is progressively affecting European policy and course of action, while the United States focuses on smart manufacturing [126].

Zhong et al. (2017) notes that the terms smart manufacturing and Industry 4.0 become synonymous today [143]. While machine tools have used computer control and networking for half a century, as noted in the historical perspective, smart manufacturing is distinct in the scale of data, controls, and connectivity in use and by the use of data to continually alter or refine a manufacturing process and throughout the supply chain [143]. Davis et al. (2012) defines smart manufacturing as the use of intense networked information throughout a supply chain [20]. Toa et al. (2018) defines the goal of smart manufacturing as being able to "convert data acquired across the product lifecycle into manufacturing intelligence in order to yield positive impacts on all aspects of manufacturing" [125]. Smart manufacturing is also characterized by the wide use of internet of things (IOT)-enabled devices, cloud computing, cyber-physical systems (CPS), big data analysis (BDA), and information and communications technology (ICT) [143].

Zhong et al. (2017), Cheng et al. (2018), Grieves (2005), Kusiak (2017), and Tao et al. (2018) discuss the challenge of creating a generic smart manufacturing framework to include design, machines, monitoring, control, and scheduling [15][34][58][125][143]. Using the large amounts of data created in smart manufacturing will require new algorithms and possibly artificial intelligence [1][130]. Alcacer and Cruz-Machado (2019) stated that companies will need to develop cybersecurity measures for data sharing along supply chains. The industry is vulnerable due to infrequent security updates, old devices, and multiple data pathways. They also note that Industry 4.0 data is uniquely valuable [1].

Davis et al. (2012) states that smart manufacturing leads to a dramatic change in the business structure due to increased responses to demand and product design changes. As a real-time ‘understanding, reasoning, planning, and management’ tool, smart manufacturing needs sensor based analytics, modeling, and simulation [20]. Current examples of smart manufacturing exist at Proctor and Gamble and Tata Motors. P&G uses production simulation to help plan bottle design.

2.1.2.2 RQ2. What are the key technology drivers of digital transformation in industry?

Many technological drivers are key in the development of a digital transformation plan (Figure 2.2, page 48). These key drivers are summarized below.

2.1.2.2.1 Cyber Physical Systems

The term cyber-physical systems (CPS) denotes a new cohort of systems with integrated computational and physical capabilities that can interact with humans through many new modalities [4]. A Cyber-Physical System embeds computers and networks that monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice-versa [62]. Thus, cyber-physical systems are real-time systems [115]. Many challenges have been identified during the implementation of CPS. These challenges can be clustered into six major areas: (1) CPS Capabilities, (2) CPS Management, (3) CPS Engineering, (4) CPS Ecosystems, (5) CPS Infrastructures, and (6) CPS Information Systems [65].

2.1.2.2.2 Industrial Internet of Things

The Internet of Things (IoT) is a network of physical "things" (objects) that are digitally connected and can sense, monitor, and interact within a business and between the business and its supply chain [9]. IoT allows information to be timely and accurately collected and transferred through the network [92]. This enables agility, visibility, tracking, and data/info sharing to expedite well-timed planning, control and coordination. The cyber-physical system (CPS) network can act to connect people, "things" and physical processes over the IoT network [17].

The Industrial Internet of Things (IIoT) is the application of IoT in the manufacturing industry [53]. IIOT has resulted from the convergence of industrial technologies and IP-enabled low-power wireless networking technologies [24]. IIOT is principally concerned with communication and inter-connection between machines (M2M) and things [31].

2.1.2.2.3 Digital Twin

Industry and academia describe digital twins in many diverse ways [29]; however, it is commonly accepted that a digital twin is an integrated multi-physics, multi-scale probabilistic ultra-realistic simulation of systems or products which can reflect the lifecycle of its parallel twin using existing physical models, history data, and real time data [32]. Rosen et al. state the digital twin is the model which can interact amid autonomous system behaviors and the environment in the physical domain [99]. Therefore, the digital twin is developed and established in conjunction with its physical twin and remains its virtual counter-part through the whole product lifespan; including the properties, condition and performance of the real-life object through models and data [36].

The first use of digital twins was for airplanes and the aerospace industry. Tuegel et al. (2011) and Glaessgen and Stargel (2012) describe this use of digital twins of individual aircraft rather than of manufacturing processes [128][33]. The digital twin they describe will be updated with data from the actual aircraft to help improve lifespan and maintenance predictions using big data analysis. Tuegel describes the challenge of multi-physics modeling where solution methods of different stressors, such as temperature and physical forces, are modeled together. Glaessgen and Stargel state that current predictions for maintenance intervals and analysis of damages are based on heuristics, factors of safety, and similitude, among others. The accuracy of these methods is based on previous experience and experimentation. However, since each aircraft and damage incident are unique, the predictions and analyses must be conservative, leading to the use of extra weight and materials. The digital twin would be linked to the real aircraft through on-board sensors to increase safety and reliability. Kritzinger et al. (2018) describe two variations of the digital twin based on the flow and direction of data transfer [57]. The Digital Model is an informational model of the physical system, but without any data interchange. The Digital Shadow is an informational model that is updated by changes to the physical system, but which does not influence the physical system.

While the digital twin was at first descriptive, it is now actionable and will allow the user to design and test the virtual version to discover manufacturability and modes of failure [35]. The digital twin is defined as an ultra-high-fidelity simulation by Alcacer and Cruz-Machado (2019) [1]. They note its importance to Industry 4.0 through simulation to all product lifecycle phases and through the inclusion of real-life data. Similarly, Tao et al. (2018) defines digital twins as the ultra-high synchronization between the physical product and digital twin, which includes multi-physics modeling [124]. Greives (2005) argues that digital twins are needed for additive manufacturing development since design in that field is more iterative [35]. As described by Padovan et al. (2019), the digital twin can also be used for knowledge as a service [85]. The service would act as an online help service based on a digital twin with historical and real time data. They developed a 'knowledge navigator' for tutoring, what-if scenarios, and augmented assistance using QR codes for diagnostics.

Greives (2005) argues that digital twins can replace physical resources that are currently wasted such as energy, materials, and time [35]. The simulation of manufacturing can reduce trial and error. He argues that digital twins would allow operators to "front-run" a system to see how an unusual situation may develop, and that this ability could have helped avoid disasters such as the BP oil spill and Chernobyl.

Finally, Greives (2005) notes issues including simulating physical laws and re-integrating the solution back into the digital twin [35]. Solution methods often require abstraction; the loss of detail may make it difficult to update the original digital twin's state.

Lee and Park (2014) stated the virtual device models needed in virtual commissioning require a geometric and kinetic model, as well as a logical model [61]. The geometric and kinetic models are generally built in CAD software, and this methodology is relatively well understood. Several methods have been proposed to create error-free logical models. These logical models should follow the input/output architecture of the real devices, commonly expressed in PLC ladder-logic programming. Since the mechanical, electrical, and controls engineers who work on the systems do not have thorough understandings of each type of model, new methodologies to help each type of engineer should be developed.

2.1.2.2.4 Digital Factory and Digital Ecosystems

The digital factory is defined as a system of digital models, methods, and tools, which are integrated by a data management system [135]. The objective of a digital factory is to secure products and processes during the primary phase of development and likewise to accompany the advancement of products and production processes with the use of digital models and simulations [12]. Hence, the key purpose of the digital factory is to support the planning process with a series of tools, such as 3D modelling programs or simulation programs [145].

Digital ecosystems are networked architectures and collaborative environments that address the weakness of client-server, peer-to-peer, grid, and web services [11]. A digital ecosystem generates a digital environment for networked groups to support teamwork, the knowledge sharing, and the development of open and adaptive technologies [129]. A digital ecosystem is inhabited by "digital components" which evolve and adjust to local conditions thanks to the re-combination and evolution similar to biological ecosystems [114]. Digital components can be software components, applications, services, knowledge, business processes and models, training modules, contractual frameworks, and law [129].

2.1.2.2.5 Smart Factory

A Smart Factory is a manufacturing solution that delivers flexible and adaptive production processes. A smart factory will resolve issues rising in a production facility that has dynamic and fast changing boundary conditions and operates in a world of growing complexity [94]. The smart factory is necessary to attain advanced manufacturing benefits based on network technologies and manufacturing data [14]. In the smart factory, the digital factory should be integrated with its real-time data, inferred statistics and information [116].

2.1.2.2.6 VR/AR/MR

Virtual Reality (VR) can be defined as a synthetic or artificial environment which provides a person a sense of reality and an impression of "being there." It has been gradually employed in numerous applications in design and manufacturing such as computer-aided design, robotics, assembly planning, and manufacturing system visualization [27]. Virtual reality is a prevailing and influential instrument that can be used to mimic and simulate real-life scenarios that are either expensive or challenging to conduct in live exercises [118].

The term Augmented Reality (AR) is often used to denote interfaces in which two and three-dimensional computer graphics are overlaid above physical objects or stations, usually viewed through head-mounted or handheld displays [10]. Promising AR applications have been created in several fields such as military training, surgery, show business, maintenance, assembly, product design and other manufacturing operations [84]. AR can deliver a seamless interface that bridges the gap between the real and virtual worlds and enhances the connections between the users and the smart environment [131]. AR in assembly guidance can help increase assembly efficiency, and as a result lower the overhead for each product [142].

Mixed Reality (MR) is the combination of a purely physical (or "real") environment and a purely virtual environment [42].

2.1.2.2.7 Cloud Computing

Cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction [42][77]. The cloud model is composed of:

- Five essential characteristics: on-demand self-service, broad network access, resource pooling, rapid elasticity, measured service
- Three service models: software as a service, platform as a service, and infrastructure as a service
- Four deployment models: private cloud, community cloud, public cloud, and hybrid cloud

A cloud infrastructure or frame is the set of hardware and software that facilitates the "five essential characteristics" of cloud computing mentioned above. The cloud infrastructure can be regarded as comprising of both a physical layer and an abstraction layer. The physical layer involves the hardware resources that are needed to support the cloud services being provided, and classically consist of a server, storage and network components. The abstraction layer consists of the software deployed across the physical layer, which manifests the "essential cloud characteristics".

The three service models that can be provided by a cloud are described as follow:

- Software as a Service (SaaS): The client uses the provider's applications running on a cloud infrastructure. The applications are easily managed from customer devices through either a thin client interface, such as a web browser, or a program interface. The client does not manage or control the underlying cloud infrastructure including network, servers, operating systems, storage, or even individual application capabilities, with the possible exception of limited user specific application configuration settings. Commercial SaaS cases: Google Apps, Dropbox, and Cisco WebEx.

- Platform as a service (PaaS): The client deploys onto the cloud infrastructure applications acquired or created using programming languages, libraries, services, and tools supported by the provider. The consumer does not manage or control the underlying cloud infrastructure including network, servers, operating systems, or storage, but has control over the deployed applications and possibly configuration settings for the application-hosting environment. Commercial PaaS cases: Windows Azure, and Heroku.
- Infrastructure as a Service (IaaS): The provider provisions processing, storage, networks, and other fundamental computing resources on which the consumer is able to deploy and run arbitrary software, which can include operating systems and applications. The consumer does not manage or control the underlying cloud infrastructure but has control over operating systems, storage, and deployed applications, and possibly limited control of select networking components [77]. Commercial IaaS cases: DigitalOcean and Google Compute Engine.

2.1.2.2.8 Simulation

All stages of the wide-ranging lifecycle of a product are supported and sustained by numerous IT-systems often known as 'CAx'-systems [19]. These computer-based technologies (CAx), like Computer-Aided Design (CAD), Computer-Aided Engineering (CAE), Computer-Aided Manufacturing (CAM), and Computer-Aided Process Planning (CAPP) systems, are used for engineering purposes, and conventionally focused on explicit and specific modeling tasks [107]. Hence, they are used by different professional communities at different phases of the PLM cycle [73]. Integrating different CAx software packages is vital to accomplish and realize digital manufacturing and computer-integrated manufacturing [43]. Putnam et al. (2017) emphasized that a whole production system should be simulated, not just a single machine [90]. They suggest running a virtual part through a physical system to reduce wasted materials and damage to machinery during commissioning.

2.1.2.3 RQ3. What empirical evidence is there concerning benefits and impact of digital transformation?

2.1.2.3.1 Metrics and Maturity

Maturity can be captured qualitatively or quantitatively in a discrete or continuous way [55]. Maturity models are usually used as a tool to conceptualize and measure maturity of a firm or a process concerning some specific target state [112]. Many maturity models have been developed for Industry 4.0: IMPULS –

Industrie 4.0 Readiness [68], Empowered and Implementation Strategy for Industry 4.0 [60], and the Connected Enterprise Maturity Model [97].

2.1.2.3.2 Model-Based Sustainment

According to the Aerospace Industries Association, the US DoD is modernizing ways the government purchases, develops, fields, and sustains prospect weapon and defense systems. Employing the Digital Twin within Model Based Engineering (inclusive of Model Based Manufacturing and Model Based Sustainment) enables authoritative technical data, software, information and knowledge so decision makers have the right information and statistics when they need it [86].

In a model-based method, data is related with a predefined model; consequently, model-based methods are fixated on confirming a previous hypothesis (the model) based on existing data and refining scientific understanding [48]. In model-based approaches, a model is constructed using a certain methodology, for instance the dynamic data systems (DDS), and diagnosis is implemented by sensing the changes and nonconformities in the model parameters and/or the variations in anticipated system responses [70]. Furthermore, model-based methods employ an explicit mathematical model of the production plant, represented in the form of differential equations [64]. The core hypothesis behind model-based methods is the existence of a system's model, which typically consists of objects and relations amongst these objects [139].

Model-based Engineering (MBE) aims at the extensive use of models of different features of the system throughout the whole engineering workflow, ideally from the abstract design through thorough design, manufacturing, test, commissioning, and operation [28].

2.1.2.4 RQ4. What empirical evidence is there concerning challenges? And how overcome them?

2.1.2.4.1 IoT Interoperability and Security Issues

Despite the fact that the technological innovations necessary for developing individual IoT systems is already here, the challenges of the interoperable IoT ecosystems are still under investigation [141]. In the Industrial Internet of Things (IIoT), there is a strong need for a high level of interoperability among independently developed systems, often from different venders [21]. Additionally, IoT is still facing several types of attacks (active and passive) that could interrupt functionality. In a passive attack, an intruder senses the node or steals the data but it never attacks physically. On the other hand, active attacks disrupt the performance physically. Therefore, security constraints must be applied to avoid devices or machines from malicious attacks [96].

Davis et al. (2012) also described the difficulty of moving into smart manufacturing [20]. They stated that existing tools need to be adapted to remain competitive while the tools are still useful. The United States will have more difficulty adapting to smart manufacturing because of our sunk cost of current systems, and business, political, and regulatory uncertainties, while developing countries can take a greenfield approach.

Prominent in the field of model-based methods (described earlier) is the cooperative Model-Based Systems Engineering initiative of INCOSE and the Object Management Group [82]. The International Council on Systems Engineering (INCOSE) describes Model based system engineering (MBSE) as a formalized application of modelling to support system requirements, design, analysis, verification, and validation activities beginning in the conceptual design phase and continuing throughout development and later lifecycle phases. One of the most important challenges when considering MBSE of IoT systems is model mapping and transformation, arising from the complex interoperability requirements in IoT ecosystem [141]. The primary goal of an MBSE approach is to capture inter-relationships in the complex system at different levels of abstraction, which supports a shared reference for diverse models and datasets [76].

2.1.2.4.1.1Data Issues

Since smart manufacturing is a method in which information is used to update and adapt manufacturing in real time throughout the supply chain and in all scales of industry, large amounts of data will be created, and the large amounts of data created by sensors will need to be used effectively [143]. Cheng et al. (2018) states that this data will be more than current manufacturers are used to handling [15]. Therefore, data mining techniques should be used to find patterns and useful information. The current data mining techniques are not capable of processing so much data. Kusiak (2017) notes that engineering and business schools rarely teach data science [58]. Companies do not know what to measure, and data is not stored in a manner convenient for modeling. This author warns that companies need to use the proper strategies to add sensors to equipment, improving data collection, and building predictive models that can handle uncertainty. He also notes that software must be designed to work across companies in the supply chain.

Hu, et al. (2018) also note that more efficient means of sharing data are needed [44]. They define the terms Cyber Physical Cloud Manufacturing (CPCM) and Cloud Based Digital Twins (CBDT). This system uses central servers to control manufacturing systems and hosts digital twins in the cloud as shared resources. This requires a large number of applications to be processed at the same time. A CPCM might control multiple factories and thousands of machines. They note CPCMs currently use standard internet protocols such as HTTP, TCP, etc. and that this can cause delay s and loss of connections. The authors created a framework using the MTConnect language to improve communication and data reliability. Preuveneers et al. (2018) suggested using software industry best practices of feature toggles and software circuit breakers [88]. These built-in software controls can enable or disable new features for testing or disable any feature automatically if it caused an error. Thus, the software can continue to run with fewer features but without crashing.

Tao et al. (2018) describe the value of data not as the volume, but the information and knowledge it contains [125]. To this end, data must be translated into information that can be understood. The "data lifecycle" is the complete journey from collection to use. Likewise, companies must design or select sensors that work well with most equipment [58].

Grieves and Vickers (2017) stated that the connectivity between IOT devices should be simulated and tested in enough detail to observe possible emergent behaviors in the resulting complex systems [35]. The authors also stated that companies using smart manufacturing will need to ensure that their data is consistent across all departments and along the supply chain.

2.1.2.4.1.2 Artificial Intelligence as Solution

Artificial intelligence has been suggested as a means to handle data in smart manufacturing. Wang et al. (2018) defines smart manufacturing as "using advanced data analytics to complement physical science for improving system performance and decision making" [130]. They state that smart manufacturing will need deep learning handle the data, and the paper surveys deep learning algorithms. However, they warn deep learning may not be good at non-structured data of different types. They emphasize users must find the right deep learning models for many different manufacturing processes.

Ever since its conception in the fifties of the last century, the field of AI has witnessed alternating periods of intense growth and significant decline [5].

Artificial Intelligence, a subdivision of computer science capable of analyzing multifaceted data [95], can be defined as the automation of tasks and processes that are linked to human thinking, for instance decision making, problem solving, learning, perception, and reasoning [46]. In recent years, features such as growing computational power and accessibility to Big Data, among others, have led to renewed interest in the field. As a result of this persistent evolution in AI research, the meaning of what is considered AI is also constantly evolving [5]. AI will still require human interaction and interpretation. Zhong et al. (2017) suggests machine learning should be adapted to include 'humans-in-the-loop' so people can direct the machine learning more effectively [143]. Wang et al. (2018) states the results of the analysis will need to be understood by engineers [130]. They suggest making generic deep learning models and models that learn incrementally, not just from one data set.

2.1.2.4.2 Emerging Standards

Standards simplify the job of stakeholders by ensuring standardization and encouraging interoperability [127]. The emergent technology of wireless sensor network has provided novel models and paradigms for factory automation that has notable impacts on control, tracking, monitoring, and diagnostics of the manufacturing processes and tools [144]. IEEE 1451 is the family of emerging standards for a networked smart transducer interface which is responsible for the common interface and supporting technology for the connectivity of transducers to control devices, and data acquisition systems [63]. The standardization and regulatory bodies such as IETF, IEEE and ETSI are critical to the technology advancement of IoT and IIoT [47]. Schleich et al. (2017) note the digital twin concept lacks a conceptual framework [110]. They propose a template for digital twins to ensure scalability, interoperability, expansibility, and fidelity. They compare existing solid modeling schemas to what could be done for digital twins.

2.1.2.5 RQ5. What role does culture play in digital transformation?

The improved inter-connectedness of businesses and entire industries is leading to ever more intertwined dependencies and is intensifying developments in distinct sectors of the economy both vertically and horizontally [6]. The focal cultural values and morals that are crucial for digital transformation success and attainment are: (1) openness towards change, (2) client centricity, (3) innovation, (4) agility, and (5) willingness to learn [39].

IT was considered as an enabler for some time, nonetheless, it has transformed, and a broader role of IT is being accepted by enterprises nowadays [87]. IT departments are provided with additional resources and responsibilities, hence Enterprise IT (EIT) governance has found a place in enterprises' priority list [132]. EIT governance is the preparation for, making of, and employment of IT-associated decisions concerning objectives, processes, persons and technology on a tactical or strategic level.

Several authors noted the need for increased education. Davis et al. (2012) describe the field as "data rich and knowledge poor" and stated smart manufacturing requires a more well trained workforce [20]. Schamp et al. (2018) noted the use of digital twins in education. The virtualization of processes and machinery allows every student to use the same virtual equipment simultaneously [108]. Mortensen and Madsen (2018) describe the development and use of a learning factory for Industry 4.0 and virtual commissioning [81]. The system is the Aalborg University Smart Production Lab. They built a virtual plant and connected it to real devices through PLCs.

2.1.3 Summary

Industries and engineering applications around the world are embracing the concept of Digital Transformation and Industry 4.0 to attain greater levels of business, asset, and product life management. This transformation is applied to all areas of a product's life cycle which involves the design, manufacturing, and use (condition-monitoring) of a product. The methodology for carrying out digital transformation must have the following characteristics: data-driven (real-time and historical data), all inclusive (analysis provides input in multiple areas of product from design to supply chain), self-learning (predictive analytics, artificial intelligence, machine learning, physics-based models), and human-machine interaction (user-specific visualizations and dashboards). This process allows for machines, systems, and users to be interconnected which allows for faster decision-making and lesser downtime. Another benefit of digital transformation is that it can be applied to a variety of industries that include general machinery, water treatment, composites, health sciences, and chemical systems.

Digital transformation has become the vision of future product creation and production engineering environments. Industry 4.0 leverages the Internet of Things (IoT) and cloud computing to create a “smart factory” consisting of cyber-physical systems that recreate a virtual copy of all machinery on the manufacturing floor as well as of the parts being manufactured allowing for the decentralization decisions. As part of Industry 4.0, emerging technologies such as virtual reality (VR), augmented reality (AR), mixed reality (MR), and digital twins create a robust methodology for smarter monitoring of processes and assets.

It is also important to note that digital transformation is not just about technology. Leaders in industry will need to foster the right culture and mix of talents to shift into a functional digital business or factory. It is imperative for users of these systems to understand digital transformation. Training and educating users are necessary for digital transformation to be implemented correctly

2.2 ROBOT AUTONOMY

Autonomy is a necessary quality for robots in many application fields, particularly when the robot has to perform in real-life settings together with other robots, and/or when the situation changes in unanticipated behaviors. Robot autonomy is also critical when employed under certain legal and moral constraints (for instance, a robot support at the hospital, or an autonomously driving vehicle on roads). Besides the dictionary and subjective descriptions, there are numerous efforts to define the term. Nevertheless, no comprehensive agreement on this matter has been reached up to now. Beer et al. present a wide-ranging investigation of current definitions in numerous fields including automation and robotics [7]. The definition of autonomy given by the authors is as follows: "The extent to which a robot can sense its environment, plan based on that environment, and act upon that environment with the intent of reaching some task-specific goal (either given to or created by the robot) without external control".

2.2.1 Automating Manual Operations

Today, any practicing methods analyst should consider using special-purpose and automatic equipment and tooling, especially if production quantities are large. Notable among industry's latest offerings are program controlled, numerically controlled (NC), and computer controlled (CNC) machining and other equipment. These afford substantial savings in labor cost as well as the following advantages: reduced work-in-process inventory, less parts damage due to handling, less scrap, reduced floor space, and reduced production throughput time. For example, whereas two operators are required for a manually operated machine tool, only one operator is required for a computer-controlled machine tool. Use of a robotic arm operating a fully automated machine tool would not even require the one operator, considerably reducing labor costs (albeit with higher initial capital costs).

Other automatic equipment includes automatic screw machines; multiple-spindle drilling, boring, and tapping machines; index-table machine tools; automatic casting equipment combining automatic sand-mold making, pouring, shakeout, and grinding; and automatic painting and plating finishing equipment. The use of power assembly tools, such as power nut- and screwdrivers, electric or air hammers, and mechanical feeders, is often more economical than the use of hand tools.

The application of automation applies not only to process operations, but also to paperwork. For example, bar coding applications can be invaluable to the operations analyst. Bar coding can rapidly and accurately enter a variety of data. Computers can then manipulate the data for some desired objective, such as counting and controlling inventory, routing specific items to or through a process, or identifying the state of completion and the operator currently working on each item in a work-in-process.

2.2.1.1 Robot use for automation

For cost and productivity reasons, it is advantageous today to consider the use of robots in many manufacturing areas. For example, assembly areas include work that typically has a high direct labor cost, in some cases accounting for as much as one-half of the manufacturing cost of a product. The principal advantage of integrating a modern robot in the assembly process is its inherent flexibility. It can assemble multiple products on a single system and can be reprogrammed to handle various tasks with part variations. In addition, robotic assembly can provide consistently repeatable quality with predictable product output.

A robot's typical life is approximately 10 years. If it is well maintained and if it is used for moving small payloads, the life can be extended to up to 15 years. Consequently, a robot's depreciation cost can be relatively low. Also, if a given robot's size and configuration are appropriate, it can be used in a variety of operations. For example, a robot could be used to load a die-casting facility, load a quenching tank, load and unload a board drop-hammer forging operation, load a plate glass washing operation, and so on. In theory, a robot of the correct size and configuration can be programmed to do any job.

In addition to productivity advantages, robots also offer safety advantages. They can be used in work centers where there is danger to the worker because of the nature of the process. For example, in the die-casting process, there can be considerable danger due to hot metal splashing when the molten metal is injected into the die cavity.

Automobile manufacturers have placed emphasis on the use of robots in welding. For example, at Nissan Motors, 95 percent of the welds on vehicles are made by robots; and Mitsubishi Motors reported that about 70 percent of its welding is performed by robots. In these companies, robot downtime averages less than 1 percent.

Furthermore, analysts should always be looking for ways to automate materials handlings to eliminate inefficient steps without sacrificing safety. One of the 10 principles developed by the MHI (Materials Handling Institute) for better material handling focuses the Automation Principle. Material handling operations should be mechanized and/or automated where feasible, to improve consistency and predictability, decrease operating costs, and eliminate repetitive or potentially unsafe manual labor.

However, a major obstacle for robot automation is robot autonomy and undependability which is expanded in the following section.

2.2.2 Autonomous Robot Capabilities

A vital problem that challenges the designer of a cognitive architecture is how to let robots access many sources of information. Several abilities discussed below give the robot access to such knowledge. For example, knowledge about the setting/environment comes through perception, knowledge about insinuations of the present state comes through planning, reasoning, and prediction, knowledge from other agents comes via communication, and knowledge from the past comes through remembering and learning (Figure 2.3, page 49). The more such capabilities an architecture supports, the more foundations of knowledge it can access to update its performance and behavior. Langley et al. (2009) summarizes the capabilities of cognitive architecture as follows [59]; in our case, this will be applied to autonomous robots:

2.2.2.1 Recognition and categorization

An autonomous robot must make some contact between its environment and its knowledge. This requires the ability to recognize situations or events as instances of known or familiar patterns. Recognition is closely related to categorization, which involves the assignment of objects, situations, and events to known concepts or categories. The robot must recognize and categorize the conveyor and the different pieces to manipulate (static), as well as the human collaborator’s movements and actions (dynamic).

2.2.2.2 Decision making and choice

To operate in an environment, an intelligent system also requires the ability to make decisions and select among alternatives. To support decision making, a cognitive architecture must provide some way to represent alternative choices or actions, whether these are internal cognitive operations or external ones. It must also offer some process for selecting among these alternatives, which most architectures separate into two steps. The first determines whether a given choice or action is allowable, typically by associating it with some pattern and considering it only if the pattern is matched. The second step selects among allowable alternatives, often by computing some numeric score and choosing one or more with better scores. Such conflict resolution takes quite different forms in different architectures.

2.2.2.3 Perception and situation assessment

Cognition does not occur in isolation; an autonomous robot exists in the context of some external environment that it must sense, perceive, and interpret. A robot may sense the world through different modalities; the sensors may range from simple devices like a thermometer, which generates a single continuous value, to more complex mechanisms like stereoscopic vision or sonar that generate a depth map for the local environment within the agent's field of view. Perception can also involve the integration of results from different modalities into a single assessment or description of the environmental situation, which an architecture can represent for utilization by other cognitive processes. An architecture that supports perception should also deal with the issue that sensors are often noisy and provide at most an inaccurate and partial picture of the agent's surroundings. These challenges can be offset with perceptual knowledge about what sensors to invoke, where and when to focus them, and what inferences are plausible. Thus, situation assessment requires an intelligent agent to combine perceptual information about many entities and events, possibly obtained from many sources, to compose a large-scale model of the current environment.

2.2.2.4 Prediction and monitoring

Autonomous Robots exist over time, which means they can benefit from an ability to predict future situations and events accurately. Prediction requires some model of the environment and the effect actions have on it, and the architecture must represent this model in memory. An ideal architecture should also include the ability to learn predictive models from experience and to refine them over time. Once an architecture has a mechanism for making predictions, it can also utilize them to monitor the environment. Monitoring also provides natural support for learning, since errors can help an agent improve its model of the environment.

2.2.2.5 Problem solving and planning

Autonomous robots must achieve their goals in novel situations, the cognitive architectures that support them must be able to generate plans and solve problems. Intelligent agents that operate in and monitor dynamic environments must often modify existing plans in response to unanticipated changes. This can occur in several contexts. For instance, an agent should update its plan when it detects a changed situation that makes some planned activities inapplicable, and thus requires other actions.

2.2.2.6 Reasoning and belief maintenance

Problem solving is closely related to reasoning, another central cognitive activity that lets an agent augment its knowledge state. Whereas planning is concerned primarily with achieving objectives in the world by taking actions, reasoning draws mental conclusions from other beliefs or assumptions that the agent already holds. To support such reasoning, a cognitive architecture must first be able to represent relationships among beliefs. A common formalism for encoding such relationships is first-order logic, but many other notations have also been used, ranging from production rules to neural networks to Bayesian networks. Note that reasoning is not only relevant to infer new beliefs but also to decide whether to hold existing ones (belief maintenance). Such belief maintenance is especially important for dynamic environments in which situations may change in unexpected ways, with implications for the agent's/robot's behavior.

2.2.2.7 Execution and action

Ideally, a cognitive architecture should also be able learn about skills and execution policies from instruction and experience. Such learning can take different forms, many of which parallel those that arise in planning and problem solving.

2.2.2.8 Interaction and communication

Sometimes the most effective way for an agent to obtain knowledge is from another agent, making communication another important ability that an architecture should support. Agents exist in environments with other agents, and there are many occasions in which they must transfer knowledge from one to another. Whatever the modality through which this occurs, a communicating agent must represent the knowledge that it aims to convey or that it believes another agent intends for it.

2.2.2.9 Remembering, reflection, and learning

Remembering is the ability to encode and store the results of cognitive processing in memory and to retrieve or access them later. Reflection involves processing of either recent mental structures that are still available or older structures that the agent must retrieve from its episodic store. A final important ability that applies to many cognitive activities is learning. Learning usually involves generalization beyond specific beliefs and events.

2.2.3 Summary

Despite the many conceptual advances that have occurred during three decades of research on cognitive architectures, and despite the practical use that some architectures have seen on real-world problems, there remains considerable need for additional work on this important topic. Most architectures emphasize the generation of solutions to problems or the execution of actions, but categorization and understanding are also crucial aspects of cognition, and we need increased attention to these abilities. Furthermore, most architectures emphasize logic or closely related formalisms for representing knowledge, whereas humans also appear to utilize visual, auditory, diagrammatic, and other specialized representational schemes. We need extended frameworks that can encode knowledge in a variety of formalisms, relate them to each other, and use them to support intelligent behavior more flexibly and effectively.

2.3 ROBOT HEALTH DETERIORATION AND FAILURE

RIA (The Robot Institute of America) has well-defined a manufacturing robot as a reprogrammable multifunctional manipulator intended to transfer material, parts, tools, or specialized devices through variable programmed motions for the performance of a variety of tasks [122]. Yet, an unexpected robot slowdown or interruption has the ability to induce a disruption all along the whole manufacturing line, resulting in financial and production losses. Readiness and maintainability, which can be defined as the likelihood of a system functioning acceptably in any time period and its ability of being repaired, are consequently crucial for industrial robots. Therefore, the automated monitoring of the robot system is necessary and looked-for, as this can enhance robot availability and maintainability and reduce operator effort. Additionally, industrial robots are highly convoluted machineries and hence the implementation of condition monitoring for them diverges from that of simple machinery. This is essentially due to the rapid changes of geometrical configuration of the robotic arm.

In addition, robot failures are costly and difficult to diagnose. Breakdown data for robot-automated production lines, collected from automotive applications, showed that nearly half of robot failures are caused by positional error. A further quarter were attributed to drive failures. Positional error may be caused by a number of mechanical failure modes or by poor tuning of the control system. Testing of repeatability or absolute position in the workplace is hard because the robot moves quickly, allowing little time for measurement. Measurement may be required in up to six axes.

To bypass stoppage, recovery stations permit production to continue whereas diagnosis and reparation of the failure/disruption progresses, by providing either a standby robot or a station where the stopped task can be completed by hand. These procedures can accomplish plant availability at the cost of either added machineries which is typically idle or by functioning at reduced manufacturing rates through these downtime phases [26]. Nevertheless, the prevailing tendencies in design of production lines is away from these procedures for the following motivations [123]:

- It is not practical or cost effective to operate with one or more spare robots on the line.
- It is not practical or cost effective to substitute a malfunctioning robot on the spot.
- The complexity of modern assembly demands that the variety of fixtures and end-effectors required makes each workstation unique.
- Substitution of a robot with a human operator has several shortcomings:
    - he or she cannot work as fast as a robot,
    - workers in an automated factory are limited in number,
    - he or she cannot be an expert in all the manufacturing operations.

Furthermore, it is not good practice to allow complex plant to run to failure because:

- Consequential damage is expensive.
- Production is lost.
- Safety is compromised

Currently, there are limited commercially existing solutions that support the automated monitoring of the components of a robot and its gripper or fixture, and consequently the capacity to unceasingly monitor the state of robots has become an significant research theme in recent years and is now getting substantial consideration [51].

Table 2.1: Distribution of selected articles (per journal)

Journal name	Number of Articles
International Journal of Production Research	17
IEEE	18
Procedia	8
International Journal of Computer Integrated Manufacturing	3
Computers in Industry	4
Others Journals	24
Conference Proceedings	10
Total	85

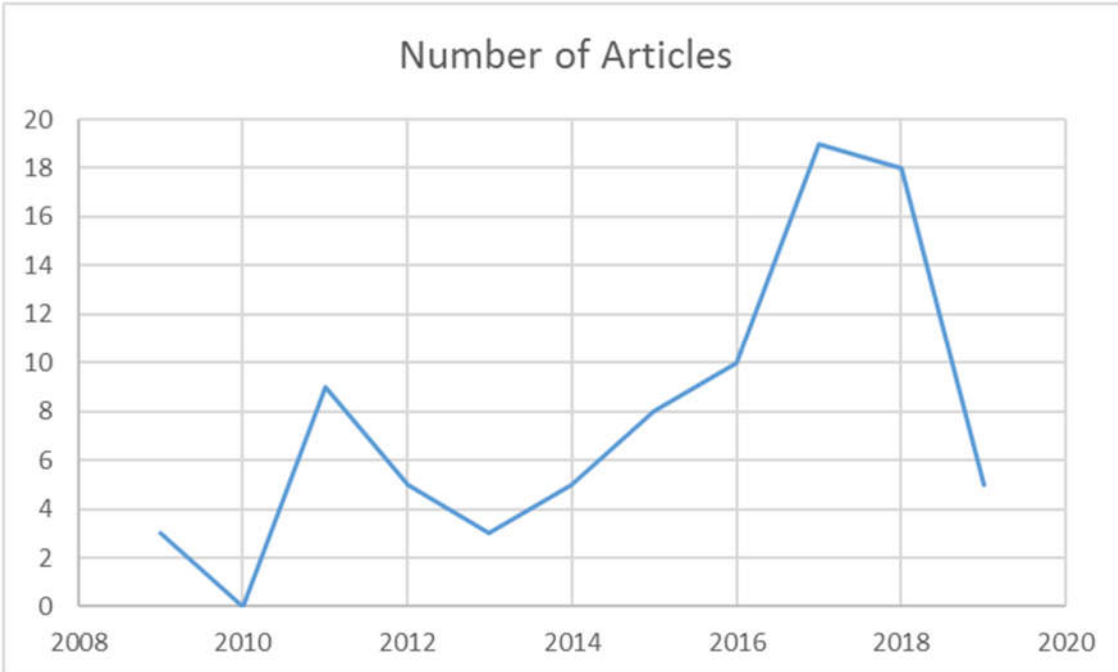

Figure 2.1: Distribution of selected articles over time

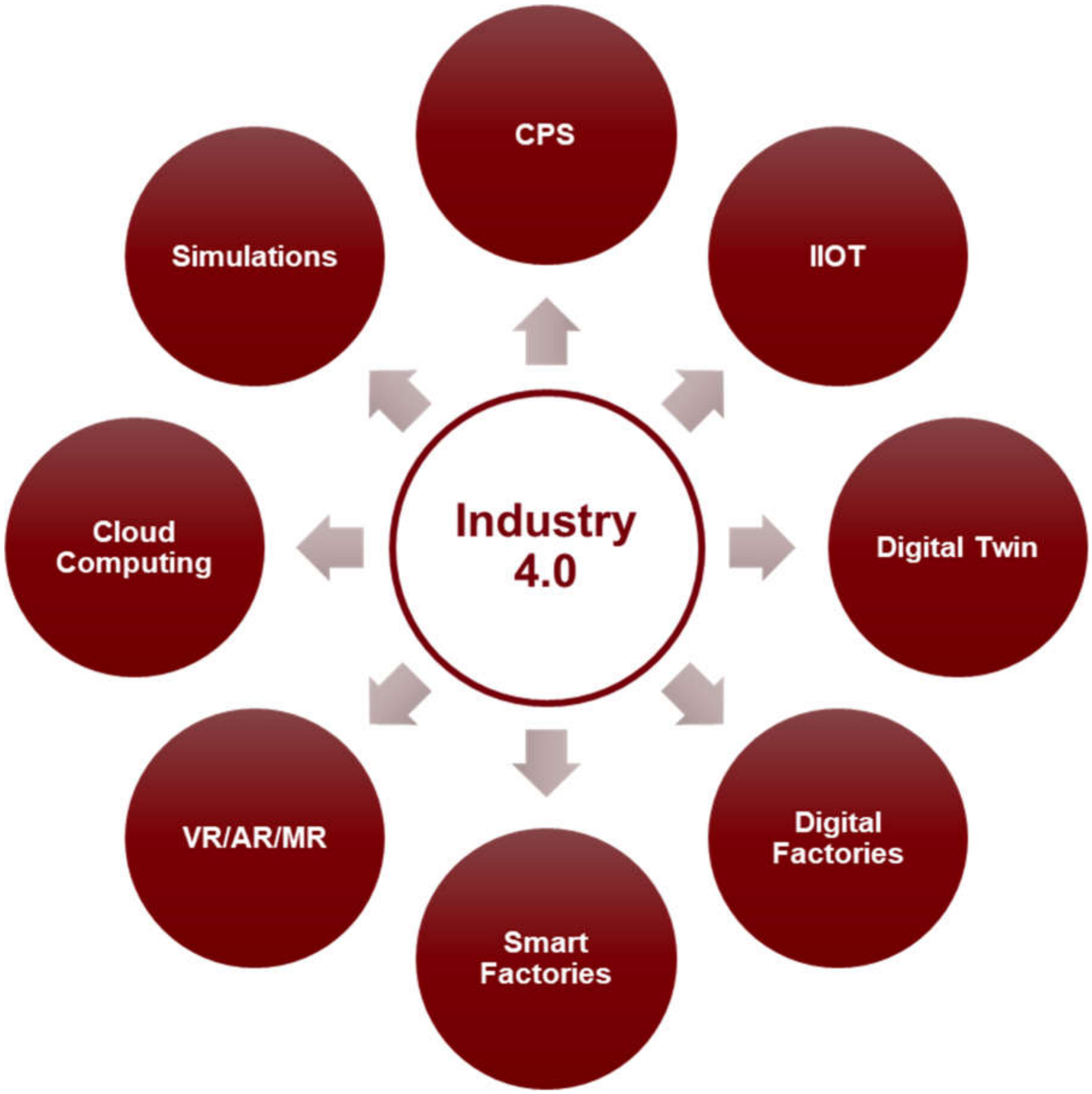

Figure 2.2: Key Technology Drivers Of Industry 4.0

Figure 2.3: Autonomous Robot Capabilities

CHAPTER 3

MULTIMODAL ROBOTIC HEALTH IN FUTURE FACTORIES

The manufacturing sector is continuously reinventing itself by embracing opportunities offered by the industrial internet of things and big data, among other advances. Modern manufacturing platforms are defined by the quest for ever increasing automation along all aspects of the production cycle. Furthermore, in the next decades, research and industry are expected to develop a large variety of autonomous robots for a large variety of tasks and environments enabling future factories. This continuing pressure towards automation dictates that emergent technologies are leveraged in a manner that suits this purpose. These challenges can be addressed through the advanced methods such as [1] large-scale simulation, [2] system health monitoring sensors and [3] advanced computational technologies to establish a life-like digital manufacturing platform and capture, represent, predict, and control the dynamics of a live manufacturing cell in a future factory.

Autonomy is a desirable quality for robots in manufacturing, particularly when the robot needs to act in real-world environments together with other agents, and when the environment changes in unpredictable or uncertain way. This dissertation research will focus on experimentally collecting sensor signals from force sensors, motor voltages, robot monitors and thermal cameras to connect to such digital twin systems so that more accurate real-time plant descriptions can be collected and shared between stakeholders. Creating a future factory based on an Industrial Internet-of-Things (IIoT) platform, data-driven science and engineering solutions will help accelerating Smart Manufacturing Innovation. Besides, this study will examine the ways of sharing knowledge between robots, and between different subsystems of a single robot, and implement concepts for communicating knowledge that are machine logical and reliable. My work will focus on applying the proposed methodology on more diverse manufacturing tasks and materials flows, including collaboratively assembly jobs, visual inspection, and continuous movement tasks (Figure 3.1, page 80). These tasks will require higher-dimensional information such as, analog plant signals, and machine vision feedback to be fed into and train the digital twin.

3.1 PLATFORM DESCRIPTION

The manufacturing sector is currently reinventing itself by embracing the opportunities offered by digital transformation, industrial internet, cognitive automation, and artificial intelligence. In the McNAIR Future Factory lab, researchers are looking to pursue the potential convergence of cyber architectures, physical manufacturing processes, and control intelligence (Figure 3.2, page 80).

3.1.1 Platform Components

Collaborative robots from Yaskawa Motoman are controlled by a safety-enabled Siemens PLC system. Industrial sensors and visual systems are embedded as smart devices to monitor the process indicators and device health states during machine operations. The cyber infrastructure is constructed based on Siemens industrial product lifecycle management software solutions, which create a high-fidelity simulation-based digital twin for the physical assembly line. The automation signals are synchronized and exchanged between PLC and the cyber systems. The researchers are also pursuing the deployable industrial AI connecting the cyber-physical system. The inspection results inferenced from multiple sources, such as industrial sensors, inspection cameras, FLIR thermal camera, and the unmanned drone, are synchronized in the control loop. The state-of-art computer vision, neural networks, and reinforcement learning are supporting the autonomous decision-makings by artificial intelligence in the cyber-physical system. Moreover, programming physical robots within the virtual commissioning platform is not only precise but also intuitive, which does not require a robotic expertise to operate. The automation signals are synchronized and exchanged between PLC and the cyber system via an OPC-UA server. Figure 3.3 (page 80) shows the actual view and the virtual view of the current platform, Figure 3.4 and Figure 3.5 (pages 81 and 82) give a glance at the planned design. Current implementations of Virtual Commissioning still require manual construction of the digital system, definition and tuning of system components. However, the development of industrial software solutions to Virtual Commissioning has greatly improved the accuracy and user-friendliness of offline programming robotic systems and verifying control logic over the traditional commissioning process. The Virtual Commissioning solution used to build the virtual cell for this work was Siemens Tecnomatix Process Simulate.

3.1.1.1 System Architecture and Data Flow

At the level of system integration, this smart data-driven system implementation workflow unfolds from three aspects. First, a virtual platform is constructed within industrial software to simulate real-life manufacturing cell behaviors. Second, towards a real-time, two-way implantation of the control loop digitalization and near real-time data communications are furtherly realized. Third, the virtual and physical system integration is driven by an intelligent scheduler while training machine learning models for scheduling optimization. This dynamic scheduler agent, termed the Digital Engine (DE) [134], is developed as a smart process optimization tool utilizing integrated platform data and applicable machine learning algorithms.

The proposed system (Figure 3.6, page 83) consists of: (1) Machine Learning (ML)- based dynamic scheduling agent Digital Engine (components in red) linked with both (2) the physical manufacturing cell (components in orange) including sensors, PLC controllers, middleware control components and other actuators, and (3) the virtual manufacturing cell (components in blue) accommodated by selected industrial simulation software, enabling the testing and commissioning of control logics and programs to be pushed to the physical plant. The communication of the proposed system requires information flow between three ends as in Figure 3.6.

Beyond simulation-based virtual cell construction, data communication between systems is one of the other major topics in creating an interactive model. Depending on the types of controllers and interacting environments in the control loop, system commissioning is categorized as real commissioning, hardware-in-the-loop commissioning, reality-in-the-loop commissioning and constructive commissioning. In particular, Virtual Commissioning control loops, under the assumption of interacting with virtual environments, are classified as "hardware-in-the-loop" and "software-in-the-loop" depending on whether physical components such as PLCs and HMIs or their virtual counterparts are connected to the simulations. In this model, the fusion of data from physical and virtual sources is proposed to be realized in two manners. First, with the philosophy of Virtual Commissioning being the capability to virtually validate system engineering, an intuitive data fusion occurs in a sequential manner, which means the digital twin, as a surrogate system, to upfront check system data resides in object dimensions, robot dynamics, signals, control logics and executed programs before they flow into the physical system implementations. This approach is described in this work as an importance-weighted data integration process. Second, beyond the conventional virtual commissioning approach, our proposed system, which is driven by machine learning modules, enables a pathway to convert unprocessed, complex and unclean real-word data to semantic communications among PLC control logics. The classification and pattern recognition capabilities of machine learning algorithms will be further utilized in the industrial decision-making process in a timely manner. To that end, specific data inference models will need to be developed, trained and validated by different datasets that can be potentially amplified by virtual data. This manner of data fusion by hybridizing physical and virtual datasets for specific manufacturing processes will be further pursued in our subsequent work, which is enabled by the data communication scheme in this proposed implementation.

The main industrial control loop in a physical cell is administrated via a PLC, which centralizes all the control logic flow between lower level components. Advancements in control paradigm typically necessitate reworks in current physical configurations, including redesign, rewiring and reprogramming of physical PLCs. To cope with this, we implement a similar philosophy of cyber-physical system based modular factory for the goal of easily customizable and reconfigurable control modules. To evaluate control feasibility and effectiveness, control scheme simulations as a digital counterpart of the physical control loop need to be developed.

Our physical cell components of the platform include sensors, actuators, middleware controllers and a S7-1500 PLC (Figure 3.7, page 84). Middleware controllers are chosen to control specific actuators, end effectors or lower-level control objects, for example, YRC1000 controller is the master of the HC10 robot. The communication between S7-1500 and YRC1000 robot controller is achieved through a Siemens CP1616 PROFINET board. Siemens TIA Portal as the automation software platform to program Siemens PLCs, including modules as WinCC and Step7, can also create HMI screens and allow access to the OPC server from a PC. The physical control loop over a robot is presented in Figure 3.8 (page 85).

During the control process, downloaded programs are executed by PLC cyclically scanning and compiling sequenced rungs, usually as ladder diagrams. When these programs are directly compiled and tested on physical setups, their debug process is often difficult and time consuming, as the PLC is potentially giving or receiving faulty commands to the physical system. Hence, Virtual Commissioning provides a methodology that can interact with the digital twin not only by performing process simulations, but also by virtualizing the control loops.

The control loops of Virtual Commissioning components are described in Figure 3.9 (page 86). By which means, programmers are able to expect the system responses from the digital twin by downloading untested logics to either physical PLCs ("hardware-in-the-loop") or the simulated PLC ("software-in-the-loop"). The "hardware-in-the-loop" implementation consists of the following components: physical PLC, OPC server and OPC clients. OPC server/client pairs are software interface standard enabling PC to communicate with industrial hardware devices. OPC server converts the hardware communication protocol used by PLCs to OPC protocols. OPC server is accommodated in S7-1500 and can be accessed by OPC clients such as Process Simulate, which connects directly to digital cell signals. On the other hand, a "software-in-the-loop" implementation in Figure 3.9 presents a software-only control loop that includes the virtual counterparts of the physical components: simulated HMI, PLC simulator, OPC server and OPC clients. The difference between "software-in-the-loop" and "hardware-in-the-loop" lies in whether simulated PLC and HMI are used instead of physical PLC and HMI. "Software-in-the-loop" excludes the usage of hardware components in the loop of two-way communications between physical and digital counterparts by routing the signals through the OPC server and the PLC simulator, where the programs can be executed within a software environment that matches the behavior of a real PLC. By this route, control safety and feasibility can be evaluated in the virtual environment before downloading to physical PLC. Hence, the digital counterpart of the control loops is achieved by simulating both PLC functions in PLCSIM Advanced and Human Machine Interfaces in WinCC Runtime. Therefore, the proposed model is realized not only in system modelling and simulations, but also in the digital transformation of control and connection pathways.

3.1.1.1.1 Remote Human Interface via OPC Server

Although adaptive intelligence demonstrated its control capability for process that follows a sequence of predefined steps in a fairly controllable environment, human still remain superior at adapting unforeseen changes in complex environment. Supporting cognitive "social human-in-the-loop" is identified as a manufacturing control architecture for future smart factories. Currently at an early stage of manufacturing intelligence, human interventions must be reliably enabled for automation systems considering limited prognostic knowledges of unexpected incidents such as equipment failure, or manufacturing strategy changes ordered from multiple stakeholders. Besides the characteristics such as autonomy, fully automation and proactivity, it was determined by Mittal et al. that context awareness, interoperability and compositionality are more commonly used to classify a system as a Smart Manufacturing system. The integration of heterogeneous and independent systems as a network for a common goal of robustness, performance or cost is also defined as "System-of-system engineering". Supporting technologies such as cyber-physical systems and Industrial Internet (IIoT) are emphasized in this context. In this work, interfaces developed in proposed implementation also concern remote human interventions and monitoring over automated systems following current industrial practices and protocols.

Typically, in automation systems, safety logics and signals such as emergency stops designed to immediately terminate machine operations are not preferably administrated by users. As they are engineered to effectively prevent system damage, one should not allow their remote access and always remain the same settings by original equipment manufacturers. As network delay and potential unreliability raise some potential concerns. For this reason, the remote access applications are urged to exclude any signals and logics related to safety.

Such as, the emergency stop must always only rely on a local physical HMI machine, even if it is possible to remotely control e-stop buttons. For a single robot system, external robot signals that operators should be safely allowed to interact with are: External Servo on/off, Safety Speed Enable, Play/ Teach Mode Select, Master Job Call, External Start, External Hold, Job Start, Robot Return Home, etc. Hence, a local customized virtual HMI is designed (Figure 3.10, page 87) using SIMATIC HMI simulator within TIA portal. Each of the robot signals is mapped to a memory registered inside OPC Server that can be written to and read from by HMI simulator. To enable a remote-control pathway, OPC server is directly accessed online by extending a python implementation of OPC client FreeOpcUA. A PC end GUI is designed as Figure 3.11 (page 88). Connecting these signals with an online space can serve as an initiative IIoT platform application available to different user ends. Further efforts will be made by our subsequent work to provide features such as smart interactions, enhanced cyber security with hierarchical log in and management authorities, and online database maintenance. For instance, concerning an application of automation security, the physical HMI should override changes made by any HMI simulator locally or remotely. Meanwhile, a local HMI should override any changes made by remote HMI.

3.2 GRIPPER HEALTH MONITORING

Pneumatically driven actuation systems and robotic grippers have an significant role in several automated manufacturing processes. Compressed air offers the essential energy, providing high power-to-weight and cost-to-benefit ratios, supporting their use in many industries including automobile, electronic, pharmaceutical, and material handling. The deployment of such devices has facilitated the automation of many production processes where they are commonly used to perform tasks that consist of repetitive actions that are often undertaken at high speed with a high degree of accuracy especially in so called “pick and place” operations. In this context combinations of linear actuators and two-finger parallel grippers are widely used [89].

The method projected in this document has been established as being able to provision improved control tactics for these systems with its ability to monitor and optimize the process.

3.2.1 Gripper Sensing

Modern manufacturing is moving towards a considerably more connected future. The integration of data, particularly live data, in the context of production will be a key motivator in future factories. Additionally, with the rise of Industrial Internet of Things (IIoT) platforms, the possible applications for utilizing live data in manufacturing are various.

By implementing modern data analytic techniques such as machine learning and digital twins, comprehensive and predictive health models can be generated to provide critical information about current operation, required maintenance, and detailed task analysis (Figure 3.2, page 80).

Five sensors are installed into a robotic gripper. Each sensor monitors, and records data acquired from different components of the robotic gripper. The data collected from the sensors is transferred to a website to be processed and paired with a camera live feed. The data then will be able to be transferred to different media so the robotic systems health can be displayed and monitored. This application provides a better real-time representation of the robotic system's health and will allow the user to act proactively. Figure 3.12 and Figure 3.13 (pages 88 and 89) depict all five sensors used on the gripper.

These sensors attached to the robot will help derive some important Key Performance Indicators (KPI) showing the health of the gripper. Each metric has a target and fallback value that will be used as parameters when designing and testing the product.

3.2.1.1 Fault Detection

With the sensors mounted on the end of the robot, many faults that can occur in the system can be detected. Figure 3.14 (page 90) shows three consecutive tasks of gripping a cylindrical object. In the first two trials, the linear potentiometer detected a signal change however the load cell did not. In the third trial, we notice that both the load cell and the linear potentiometer detected the grip on the object. With such control on the gripper, the virtual commissioning model can be trained to detect when a gripper misses the part and grip to nothing and take corrective action. The linear potentiometer gives an illustration of the status of gripper opening and closing; however, the addition of the load cell could help in detecting and monitoring if the gripper in fact gripped onto something or just in the air.

On the other hand, another experiment was also conducted to test the detection of object slippage while gripping. Figure 3.15 on page 91 depicts 4 consecutive tasks where the gripped first gripped onto the part, then lost grip totally (tasks 1 and 2) or partially (tasks 3 and 4). These detections can be reinforced using control loops and embedding them into the virtual simulation.

3.2.2 Mathematical Concepts for Health Monitoring Modelling

3.2.2.1 Support Vector Machine (SVM)

This concept for the health model component of the design utilizes a supervised machine learning approach. Incoming data from the robotic arm or the digital twin can be used to train the SVM, which takes advantage of the real-time aspect of data collection using online learning. This means that the model will continuously train and become more accurate during operation. By correctly categorizing pre-labeled sensor data as in-bounds or out of bounds, this model aims to generate ideally located hyperplanes which provide context and meaning to the data. These hyperplanes can be N-dimensional, allowing for any or all of the individual sensor data streams to be compared and analyzed for maximum predictive ability. The purpose of the model is to conduct precision deterioration detection and health monitoring for the robotic arm. In general, the health degradation monitoring methods might be divided into three main kinds, that is, model-based method, data-driven method and qualitative knowledge-based method. Owing to the nonlinearity and uncertainty of degradation process and the complexity of failure mechanisms, data-driven methods are much easier than the other two kinds of methods in terms of implementation. Support vector machine (SVM), as a data-driven method, determines an optimal hyperplane to define a decision boundary which separates input data points into different classes. SVM has an irreplaceable advantage in solving the problem of small sample, high dimensional and nonlinear classification. Hence, SVM has been extensively used for fault diagnosis and health degradation monitoring.

Multidimensional feature extraction is achieved to reflect the various characteristics of degradation process from different aspects, via the integration of time domain features extraction based on time domain statistical analysis, and frequency domain features extraction based on power spectrum analysis based on the type of data and it's source from the gripper. Raw sensor signals cannot be directly utilized to accomplish health degradation monitoring of machining tools because of the contained redundant information with noise. To detect and track the evolution of nonlinear and stochastic degradation processes for machining tools, multidimensional features for the health degradation monitoring are generated by analyzing time domain, frequency domain and time-frequency domain of the preprocessed sensor signals.

3.2.2.2 Back-Propagation Neural Network (BPNN)

Our second concept for the heuristic health model is to make use of a Back-Propagation Neural Network (BPNN), which is a supervised (data labeled) artificial neural network (ANN). This model again makes significant use of online learning capabilities to continuously update with incoming live data streams. One advantage of the BPNN is the ability to fine tune the algorithm through adjustment of the learning rates and biases of our cost function. However, there exists the potential for overfitting or overlong learning times which could impact the predictive effectiveness of the model.

3.2.3 A non-Conventional Application of Statistical Process Control (SPC) Charts in Health Monitoring

Statistical Process Control (SPC) is a technique of gauging and monitoring quality by closely observing a given manufacturing process. Appropriate quality data is collected in the form of product measurements or readings from various machines. This data is used in evaluating, monitoring and controlling the variability of the considered manufacturing process. This section proposes the expansion of SPC methods to predictive maintenance. Applications of SPC techniques in various fields outside of basic production systems have been increasing in popularity. Furthermore, this section investigates the practicality and viability of using Control Charts in predictive maintenance and health monitoring. Moreover, this study discusses numerous enabling technologies, such as Industrial Internet of Things

(IIOT), that help to advance real-time monitoring of industrial processes. This study also expands briefly on the use of Naïve-Bayes and other Machine Learning methods to identify strong (naïve) dependencies between specific faults and special patterns in monitored measurements. Despite its idealistic independence assumption, the naïve Bayes classifier is effective in practice since its classification decision may often be correct even if its probability estimates are inaccurate. Optimal conditions of naïve Bayes will be also identified, and a deeper understanding of data characteristics that affect the performance of naïve Bayes is analyzed.

3.2.3.1 Background

Control charts are used to detect special cause variation but other tools such as Pareto diagrams or fish-bone diagrams are sometimes needed to address root causes. If the data is normally distributed, standard Shewhart control charts are used. If the data is non-normally distributed with correlation, conventional control charts give too many false alarms. Selecting an appropriate control chart depends on characteristic and attributes of data and economic factors such as sampling, testing, investigation costs [74].

The modelling of the explicit relationship between maintenance and quality of the final product has not been adequately addressed. Ben-Daya and Duffuaa's study on maintenance and quality highlights the missing link between the two and proposes a broad framework for modelling the maintenance-quality relationship.

A common feature of the existing models to determine economic production quantity (EPQ) and maintenance schedules jointly does not account for the optimization of maintenance amount. The new dimension brought to the modelling of this problem is including the maintenance effort as a decision variable to be optimized. In many PM models, system is assumed to be in new quality after maintenance, but a more realistic approach is when the failure of a system changes by assuming the system quality is between before failure and after maintenance states. However, there is no attempt in these models to optimize the PM effort to change the failure pattern in order to achieve given quality goals. One of the two proposed approaches is based on the idea that maintenance affects the failure pattern of the equipment and that it should be modelled using the concept of imperfect maintenance. The second approach is based on Taguchi's approach to quality [8].

MacCarthy and Wasusri's paper expands on the lack of connection between the failure detection patterns and maintenance processes identified in Ben-Daya's paper. It reviews and highlights the critical issues of the non-standard applications of SPC charts in articles from 1989 to 2000, classified in five categories: monitoring of non-manufacturing processes using Shewhart charts, monitoring of non-manufacturing processes using more advanced charts, deriving appropriate plans and schedules, evaluating customer satisfaction, and developing forecasting models. The articles reviewed are broken down in layered categories as below:

- Application Domain

- Engineering, industrial, and environmental applications
    - Healthcare applications
    - General service sector application
    - Statistical application
- Data Sources Used
- Types of Control Chart Technique Employed

It is shown that application boundaries of SPC charts reach beyond manufacturing. In non-manufacturing applications, the nature and scope of the process and relevant quality characteristics must be clearly defined, as well as the concepts and interpretation of statistical control states. If the assumptions underlying the Shewhart theory are violated, more advanced control charts are needed. A step-by-step, holistic guide for selecting the best type of control chart for the objective is given. It is necessary to experiment with many types of control charts because of various data characteristics [74].

Jennings and Drake further examine the non-manufacturing use of control charts and propose the development of an original method of normalizing the interdependent measurement parameters in machine tool monitoring. Since some machine tool sub-systems operate continuously, intermittently, and at various torques and speeds, the measured data during steady-state and transient tests must be normalized during pre-processing before the construction of control charts. This value will often be in error due to the error between the mean value of the group and the true value. Three-variable chart is created in a very similar fashion to the two-variable chart by using the residual values calculated from the deviation from means. The authors present these three examples of measurement normalization as a verification of their performance parameter inter-dependence compensation method [52].

The assumption of a steady state process presents an issue for the implementation of control charts in dynamic and unstable non-manufacturing applications such as predictive maintenance. Since the conventional Shewhart average level chart is not applicable when the variation is not purely random, adaptive moving charts are studied. Wang and Zhang's objective in their study is to use adaptive SPC methods based on an autoregressive model to create an adaptive control chart that does not readily assume constant steady state and normal distribution of variables. Two-stage failure criteria are used as the basis for the SPC charts. This article attempts to analyze processes where no previous knowledge is present, and the process is non-stationary and most likely non-Gaussian. The autoregression model used is basically a one-step ahead prediction based on the output values before being regressed on to the function itself. The coefficients and the error term of a linear, parametric autoregression model can be determined to levels of accuracy using published algorithms, such as the forwards least-squares algorithm. The adaptive moving average is also considered for the same vibrations data where it is found to be more conservative than the adaptive moving range method. The adaptive Shewhart average level chart is used simultaneously for all the variables and is found to be ideal because it does not need a subjective threshold level; however, it is very insensitive to small changes in measurements [25].

Yin and Makis take a Bayesian approach due to the inconclusiveness of the steady state information about process control in their 2009 publication. In this paper, design of a multivariate Bayesian control chart for condition-based maintenance (CBM) applications is considered using the control limit policy structure and including an observable failure state. On top of the Bayesian chart to optimize the probability of true alarms and to find the best sample size, sampling rate, and control limits, optimization models for economic and economic-statistical design of the Bayesian chart are developed to determine the optimal control chart parameters to minimize the expected average maintenance cost. The proposed multivariate Bayesian control chart performs better and compromises its economic performance much less than the traditional chi-square chart when probability of failure prevention increases [138]. This section proposes the expansion of SPC methods to predictive maintenance.

3.2.3.2 The Selection of Appropriate SPC

In the process of determining which SPC is more fit to our application, many aspects of the model development were assessed. Shewhart control charts (mainly $\bar{x}$ and R chart or $\bar{x}$ and s chart) are particularly useful in the first phase of an SPC application: the process is to be expected to be out of control and undergoing assignable causes that are reflected in big changes in the observed parameters. However, a main drawback of the Shewhart control chart is its use only of process data contained in the last sample observation and its unawareness of any indication given by the full sequence of collected data. This feature renders Shewhart control chart unresponsive to slight process shifts (around 1.5*s or less). In cases where the process inclines to function in control, consistent estimates of process parameters (for instance, mean and standard deviation) are obtainable, but assignable causes do not normally result in great process upsets or disturbances. This issue can be addresses by introducing other criteria to the control charts, for example warning limits and other sensitizing rules, can be applied to Shewhart control charts to improve their performance against small shifts. Nonetheless, using such measures reduces the practicality and simplicity of a Shewhart control chart understanding, and intensely decreases the average run length (ARL) of the chart when the process is in control.

An effective unconventional approach to the Shewhart that may be used when small process shifts are of interest is the cumulative sum (CUSUM) control chart. In this section, we focus on the cumulative sum chart for the process mean. First, If the process is in control at a target value $\mu 0$ (determined by training data from in-control process), the cumulative sum defined is a random walk with mean zero. On the other hand, if the mean shifts upward ($\mu 1 > \mu 0$), an ascendant shift will develop in the cumulative sum. On the contrary, if the mean swings descending

($\mu 1 < \mu 0$), then a downward shift will progress. Consequently, if a trend develops upward or downward, we should consider this as evidence that the process mean has shifted, and a search for some assignable cause should be performed. The effectiveness of such chart was tested and validated for temperature and vibration data collected in the lab. Using the CUSUM method, we were able to detect cavitation in a centrifugal pump through vibration data, and gearbox fault detection using temperature data [105].

In Figure 3.16 (page 92), the graphs are divided into 2 sections. The white section represents the training of the data (not reflected in upcoming graphs). The model was trained using normal condition data. The CUSUM calculations used to develop the graphs in Figure 3.16 how the system is in control (all points are grey and in control between H+ and H-. Once the cavitation is detected, the graph shows that the system goes out of control showing that the cavitation likely happed around the 34-35th second.

Furthermore, Data for the gearbox demo was also used to validate the CUSUM model developed for fault detection. Figure 3.17, on page 93, shows how the fault induced was detected leading an out-of-control chart.

We have observed in this paper how the CUSUM control chart was effective in sensing shifts in processes when faults were induced.

3.2.3.3 Machine Learning Approach for Condition/Fault Dependency

In our application, the process data are usually high-dimensional with multi-categorical variables, as the process are being monitored with multiple sensor signals. In such cases, one classic fault classifier to correlate categorical features with a labeled fault will be Naïve-Bayes classifier. The prediction formula is:

$$P_{(F|S_1,S_2,S_3\ldots)} = \frac{P_{(S_1,S_2,S_3\ldots)}P_{(S_1,S_2,S_3\ldots|F)}}{P_{(F)}} \qquad \textbf{(1)}$$

In Equation (1), Posterior $P_{(F|S_1,S_2,S_3\ldots)}$ represents the possibility of when signal sequence $(S_1, S_2, S_3 \ldots)$ are being observed, the possibility of the system having fault F, which could be temperature fault F_t, pressure fault F_p, vibration fault F_v or leaking fault F_l. More specifically, the faults at different components can be singled out and predicted. Prior $P_{(S_1,S_2,S_3\ldots)}$, Likelihood $P_{(S_1,S_2,S_3\ldots|F)}$ and Evidence $P_{(F)}$ can be calculated based on the fault occurrence possibilities from experimental results (Table 3.1, page 78). Note that the Bayes rule can only handle categorical data, which requires sensor signals to be categorized using above SPC Charts to decide whether each signal is located within a safe range at the current monitor time.

The superiority of Naïve-Bayes lies in that it can handle missing values well and show robustness to irrelevant feature signals. It is also a relatively fast algorithm dealing with big datasets, which is particularly important for online decision-making process.

3.3 ROBOT HEALTH DETERIORATION AND MONITORING

Robot precision deterioration detection, monitoring, and valuation are crucial activities in numerous manufacturing robotic applications, particularly when it comes to the high precision processes that may comprise assembly, welding, material removal, drilling, and riveting. The deterioration of robot precision can increase the probability of unpredicted stoppages and influence manufacturing quality and production efficiency.

3.3.1 Robot Precision Degradation

More and more precise, profitable, and flexible robotic advances are fast-tracking robot usage outside the ceaseless, high-throughput manufacturing processes [2][100][16]. Small batches and made-to-order manufacture are prevalent in robotic cells that necessitate design variations and modifications. Conventional teaching approaches are becoming outdated for they are tedious and inimitable (for instance, drilling thousands of holes on an airplane’s fuselage) [22]. Enhanced precision permits robotic technologies to empower further robotic offline programing that promotes substantial time and cost savings [79]. This growing ability similarly allows robotic advancement to be used across wide-ranging processes, like assembly, high precision welding, material subtraction, robotic machining, medicinal processes, and robotic 3D printing [140][117][109][23]. High-precision robots are becoming appreciated apparatuses for several of the abovementioned processes due to the considerable cost savings that can be attained by these novel high-tech integrations [22][23]. The current call for high-precision robots in these industrial processes has amplified the prominence of robotic precision sensing, and deterioration monitoring research [91].

3.3.1.1 Equipment and Setup

The 6 motion capture cameras were split between 2 separate 12-foot aluminum poles (Figure 3.18, page 94). They were then attached to the poles using general camera mounts and pointed in the same general direction. It should be noted the middle camera was placed on the opposite side of the pole as to attain a greater offset for more accurate tracking. The poles were then move to opposite corners of the lab. Each camera was then individually attached to a network hub placed at the bottom of each pole through an ethernet cable. One hub was daisy chained to the other one which was then connected to the laptop. 4 IR reflectors were then stuck using 3M pads to the custom gripper on the GP8 in a radial pattern (Figure 3.19, page 95). Table 3.2, on page 79, shows a detailed list of the equipment used in the experiment.

3.3.1.2 Calibration

With the cameras placed in opposing corners and generally facing towards the center of the lab the calibration process could begin. In the Motive software the calibration button was selected. Various extraneous signals picked up by the cameras were masked as to be able to focus on the calibration wand. The software then prompted to begin wanding (Figure 3.20, page 96). The wand was moved all around the lab in a controlled manner. Visual affirmation was given both by the cameras as a ring around the lens started to turn green and colorful path appeared in the camera view box in the software. After wanding, the software calculated calibration settings and an exceptional value was returned. The settings were then applied to the cameras. Next, the ground plane was calibrated by placing the calibration triangle on the ground and leveling it. By selecting the 3 points on the calibration triangle, the ground plane was set. Finally, a ridged body was created for the gripper motion capture points by using the software's ridged body creator, simply by selecting the 4 points and selecting create.

3.3.1.3 Experiment and Results

With the setup and calibration complete we could begin receiving data about the position and movement of the gripper. The position data was given relative to an origin created during the ground calibration step. A process was programmed for the GP8 using Siemens Process Simulate and uploaded to the robot. The process was then performed and recorded using the Motive Software (Figure 3.21, page 97). X, Y, Z position and error data was collected for each of the motion capture points and a generated center point of the ridged body. Furthermore, rotational data was collected. The data points were then exported as a CSV file and analyzed using excel.

3.3.2 *Cloud-Based Object Detection Near Robot*

Beyond the automation pyramid proposed by ISA-95 [3], RAMI 4.0 [72], recent manufacturing paradigms for the integration of enterprise and control systems are decomposing to networked distributed services. For example, NIST service-oriented Smart Manufacturing architecture [137] proposed the utilization of a manufacturing service bus to combine different services, such as modeling and simulation (enterprise digital factory or digital twin) services, business intelligence, and computing/control ends (real factory). By which means, the business intelligence developed as a cloud service can be deployed to each of the manufacturing processes. Enabled by cloud services, the service-oriented architectures (SOA) become commercially deployable. IBM I4.0 proposed a 2-layer decentralized manufacturing system architecture (Figure 3.22, page 98): hybrid cloud layer and device layer. In this work, image uploading and result query using Watson™ IoT platform over the IBM cloud™ are enabled by representational state transfer API (RestAPI) to extend factory's computing capability. Data are further utilized across various levels: edge, plant, and enterprise, facilitated by distributed computing power from the cloud [45].

IBM cloud™ is a set of cloud-based products for a wide range of IT applications, including database management, AI development, computing servers, IoT platforms, etc. [50]. It provides an environment that helps simplify data preparation processes and model building operations using a set of tools and machine/deep learning capabilities in the cloud. This work explores an AI development use case using Watson Studio™ and presents the system integration process including image result queries and systematic deployment. Other products will be further explored in future work.

Training deep learning models by Watson Studio™ is intuitive, simply by uploading the images and labelling them using web-based interfaces, shown in Figure 3.23 and Figure 3.24 (pages 99 and 100). The embedded cloud computing power trains the images or detects test images for regions of interest shaped by bounding boxes. Each derived model is designated with an API endpoint, which is used to query the model. Knowledge from the trained model is used to infer a result from uploaded images. The query results return a JSON file with a list of detected regions and their detection confidence scores. The authors embedded cloud-based object detection model in the monitoring devices by scripting the image query pipeline with URL syntax using Client URL (cURL) [18]. A near-synchronized human detection result fed by IP security cameras is shown in Figure 3.25 on page 101. Furthermore, using OCR (optical character recognition), we are capable of extracting text from images, thus expanding the usage of computer vision inside a manufacturing cell.

Computer vision algorithms are taught by feeding various examples of images already tagged with the needed contents to be identified by the model. Appropriate ratios of both positive and negative image sets are used for training the algorithm. In the case below, we notice an open door that is being annotated, a negative case would be to train the model with images where the door is closed.

Other than the feature of classifying images from our cell, another capability provided by Watson Studio, that we are expanding on, is object localization. Region-Based Convolutional Neural Networks (R-CNNs) [93] have been traditionally used for handling object localization. This capacity would help the operator better understand and locate undesired objects inside the cell. Localization finds a specific object's location within an image and displays the results as a bounding box around the detected object. The main challenge that arises with the use of this feature is the boundary identification problem that arises when an overlap of two or more objects occurs in an image. To remedy this problem, we are working on a solution that involves analyzing and mapping feeds from different views.

Table 3.1: Fault Occurrence and Signal Indicator form Experimental Data

Time Stamp	Sensor Signals in safe range	Temperature Fault	Vibration Fault	Leaking Fault
T_1	S_1=True, S_2=True, S_3=True…			
T_2	S_1=False, S_2=True, S_3=True…	Detected		
T_3	S_1=True, S_2=True, S_3=False…			Detected
…	…	…	…	…
T_n	S_1=False, S_2=True, S_3=False…	Detected		Detected

Table 3.2: Equipment used for tracking robot precision degradation

Equipment	Comment
1 Robot with custom gripper tool	Yaskawa GP8 Robot
6 motion capture cameras	OptiTrack PrimeX 13W
2 network hubs and 8 ethernet cables	
Laptop with motion capture software	OptiTrack Motive
Desktop with virtual commissioning software	Process Simulate
Calibration tools	OptiTrack Calibration Wand (CWM-250) and Triangle (CS-200)
4 IR reflectors	Motion Capture Markers - OptiTrack

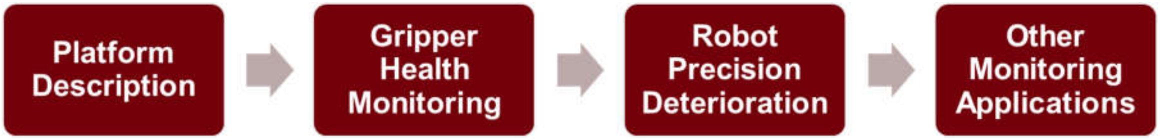

Figure 3.1: Chapter Organization

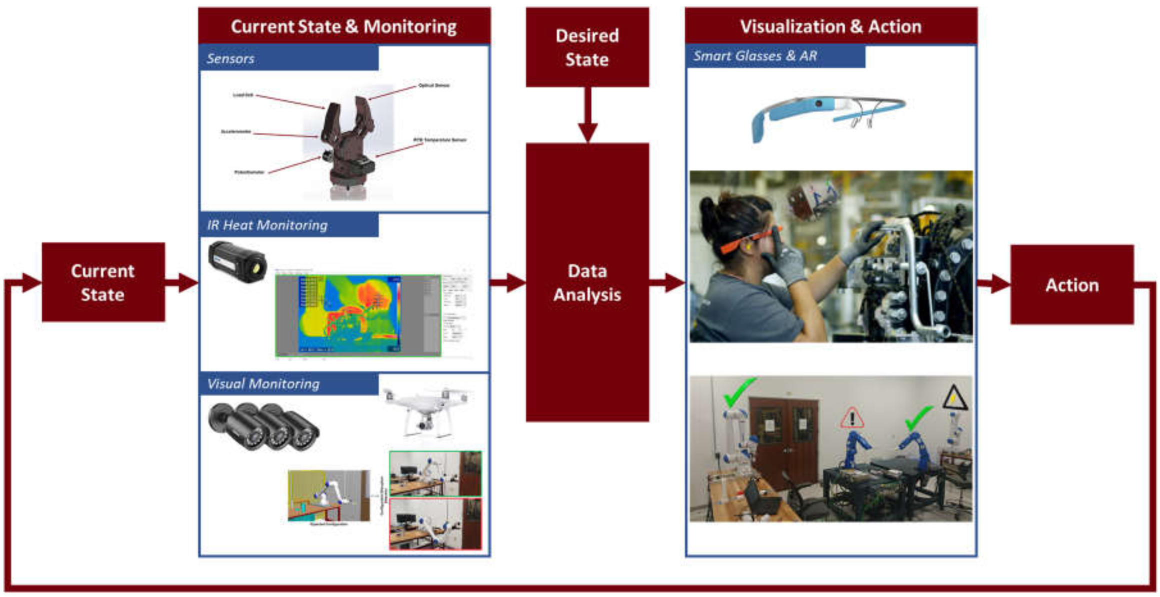

Figure 3.2: Planned Design for System Health Monitoring

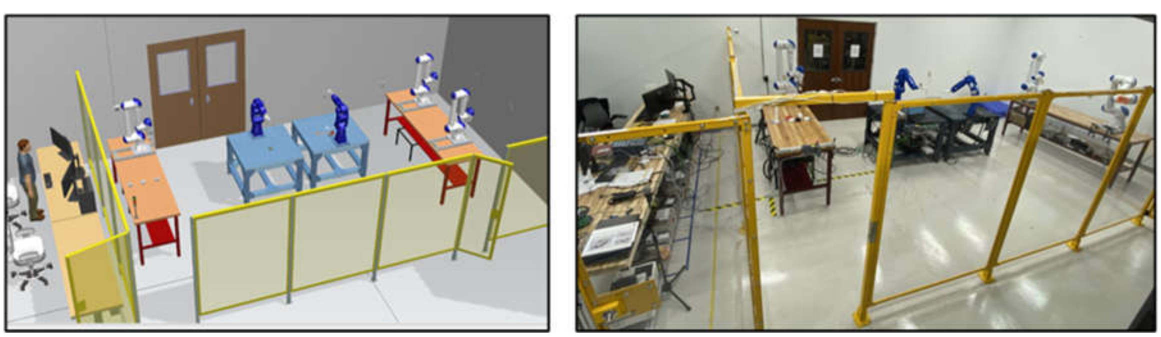

Figure 3.3: Current Platform: (a) ProcessSim View, (b) Actual View

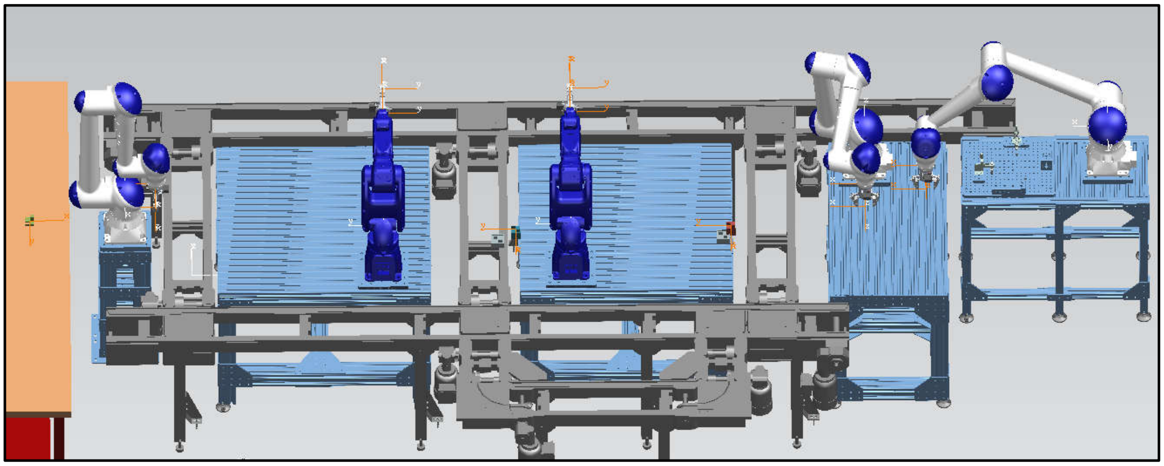

Figure 3.4: Planned Design

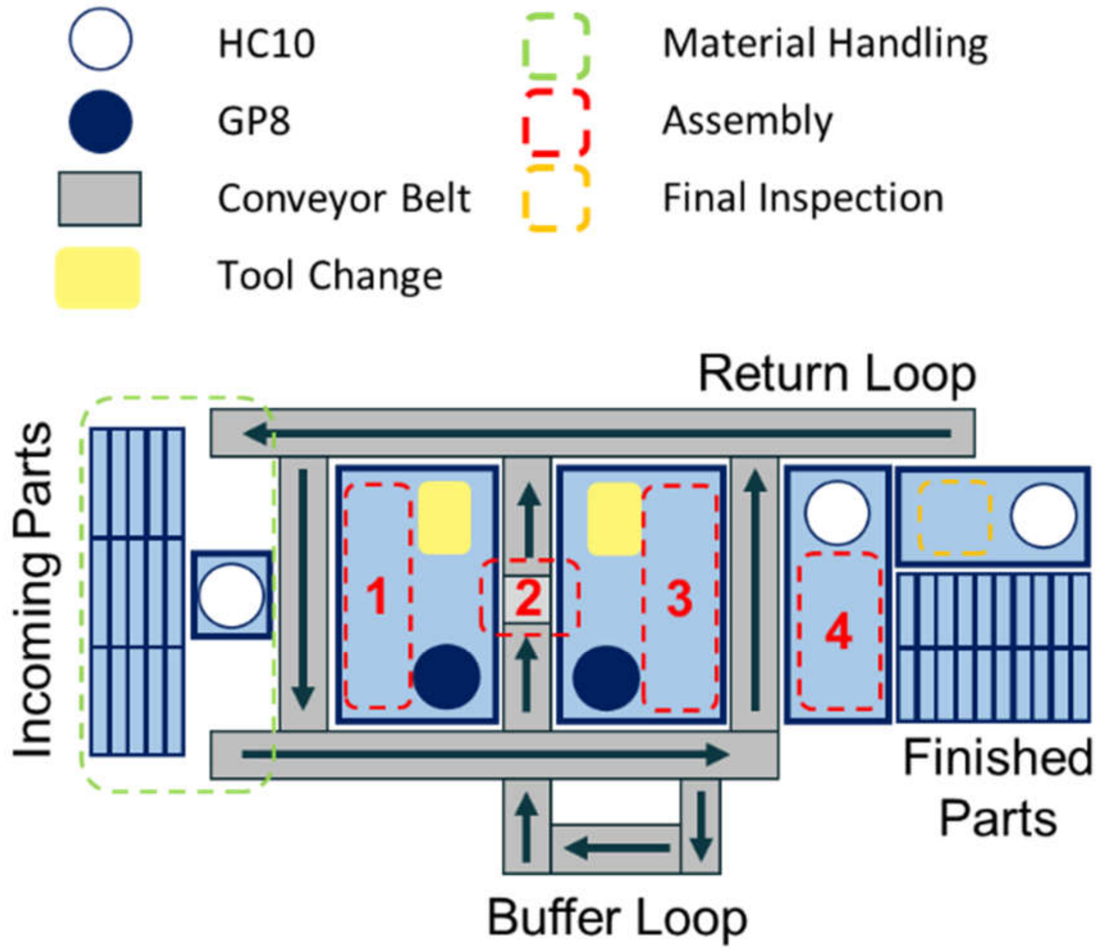

Figure 3.5: Top view of the cell design with Material Handling, Assembly, and Inspection Areas

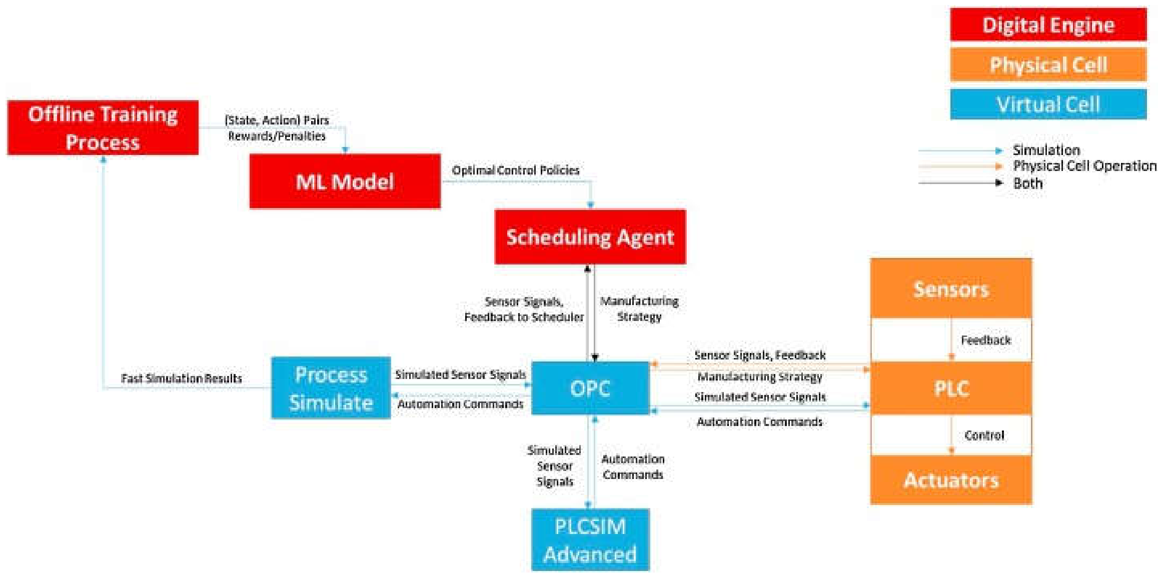

Figure 3.6: Data Flow between proposed Virtual-Physical-Scheduler System Ends

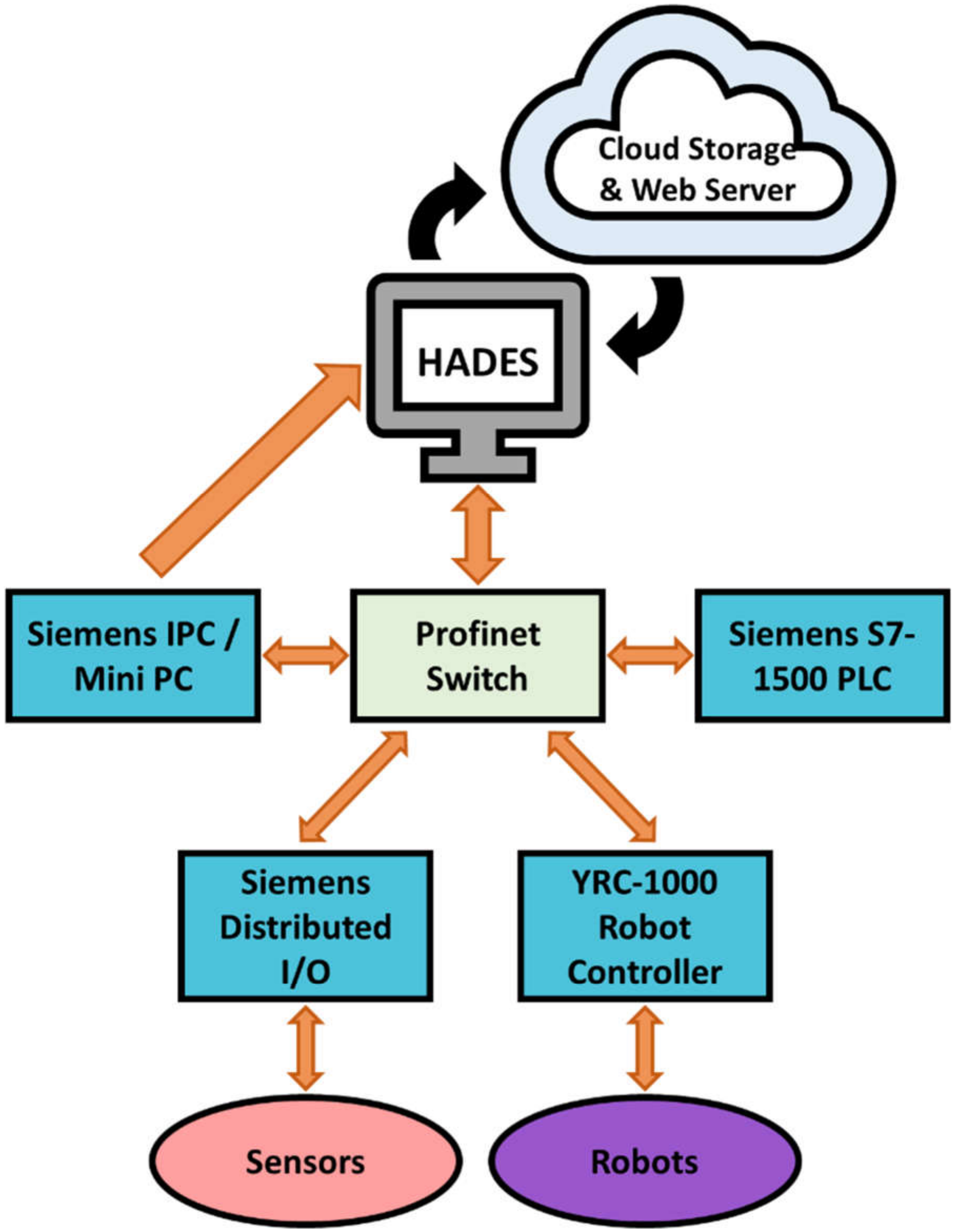

Figure 3.7: Computing Architecture

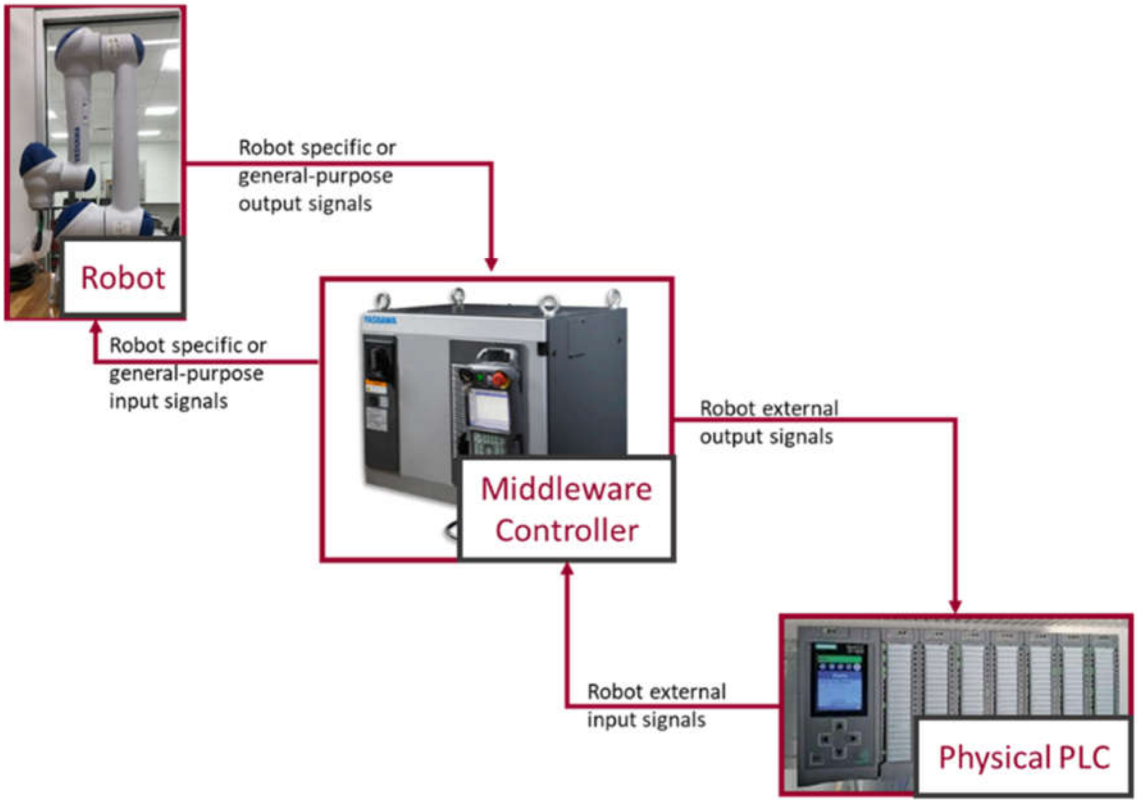

Figure 3.8: Digitalization of control loops in physical and virtual robot platforms - Robot signals hardware control loop

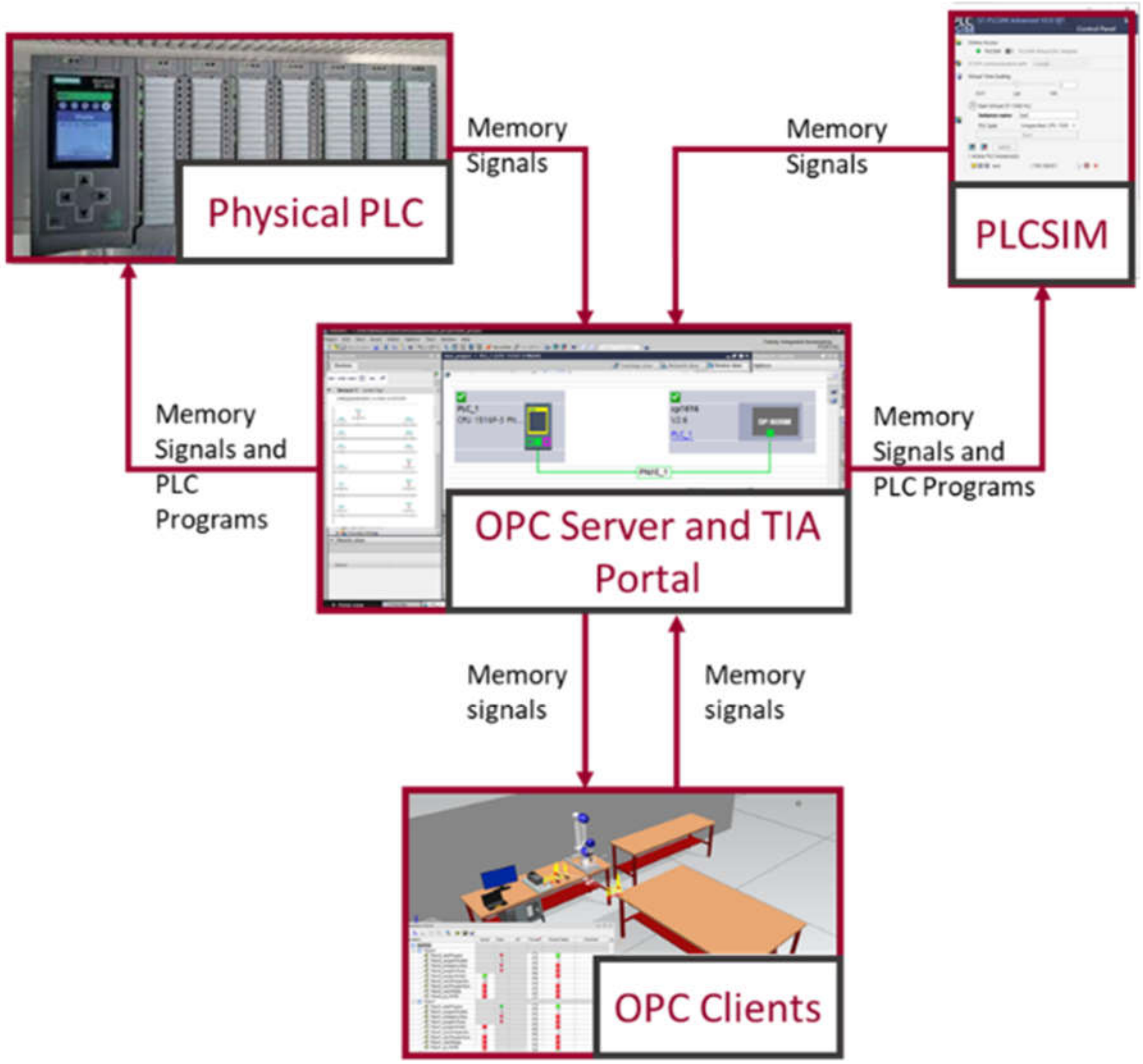

Figure 3.9: Digitalization of control loops in physical and virtual robot platforms - Virtual cell control loops by Hardware-in- the-loop (PLC as controller) and Software-in-the-loop (PLCSIM as controller)

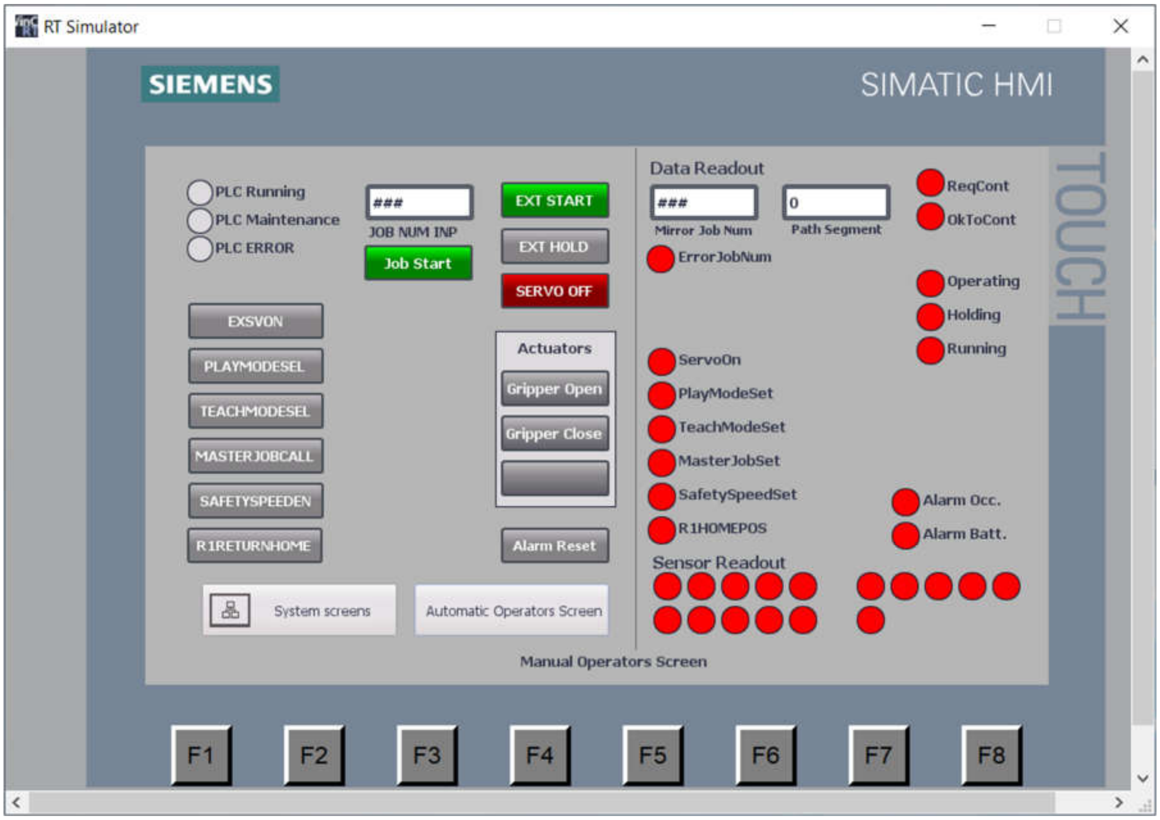

Figure 3.10: Local HMI screen

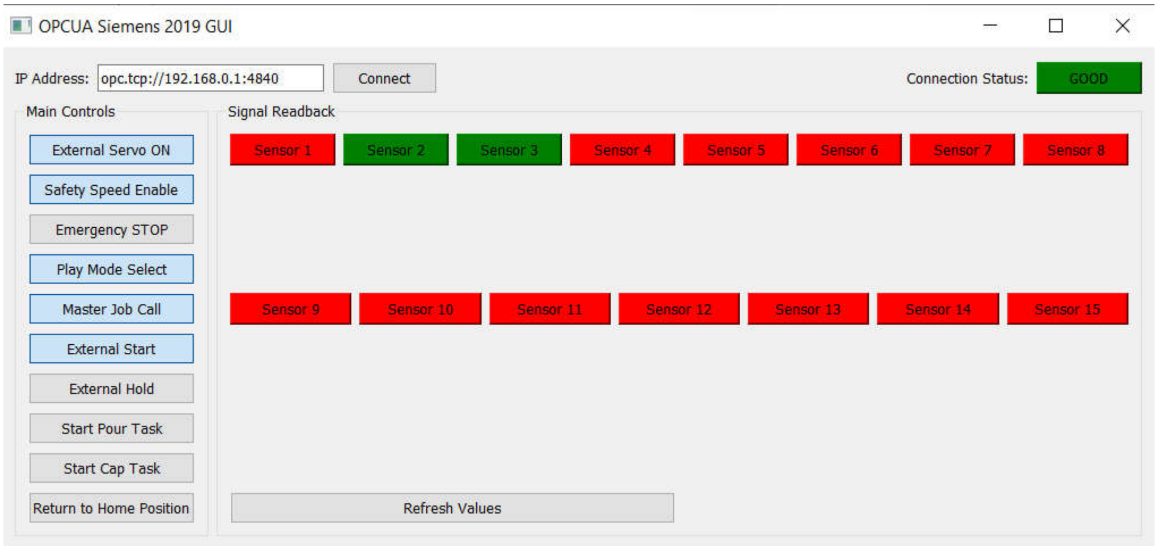

Figure 3.11: Remote human intervention screen

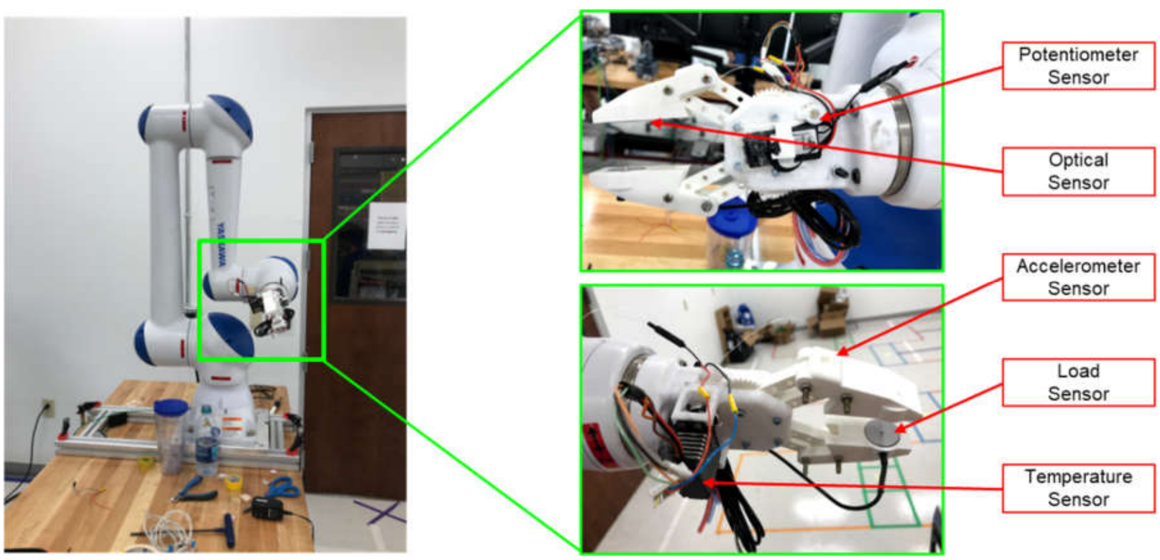

Figure 3.12: Sensors used on the Motor-Driven Gripper

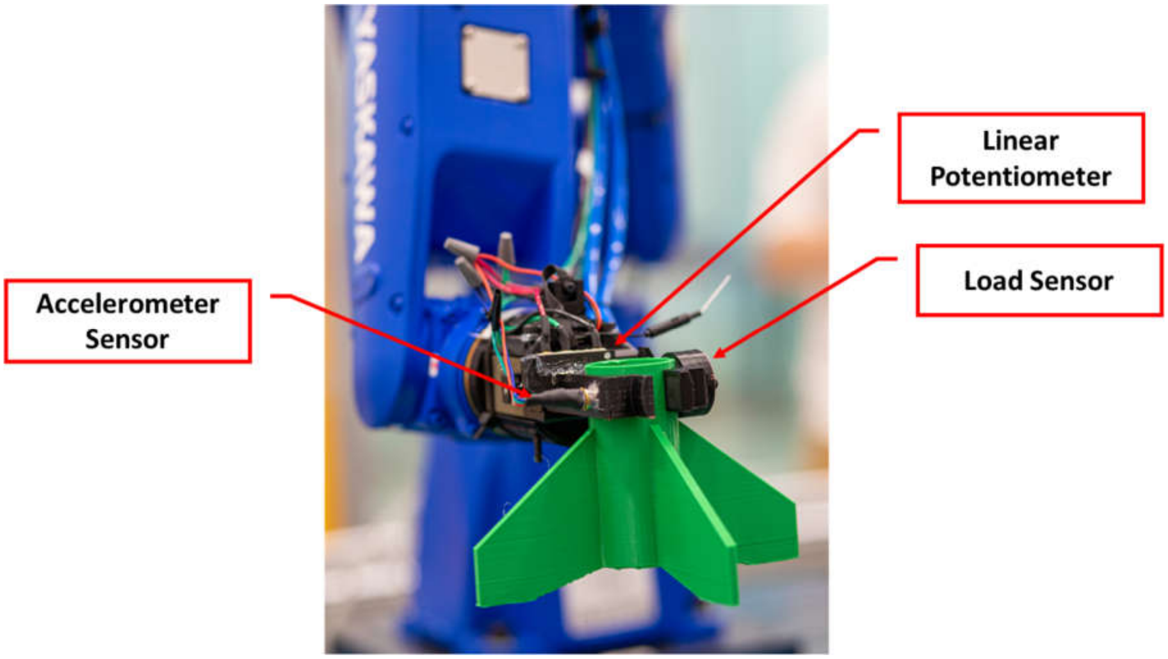

Figure 3.13: Sensors Used on Pneumatic Gripper

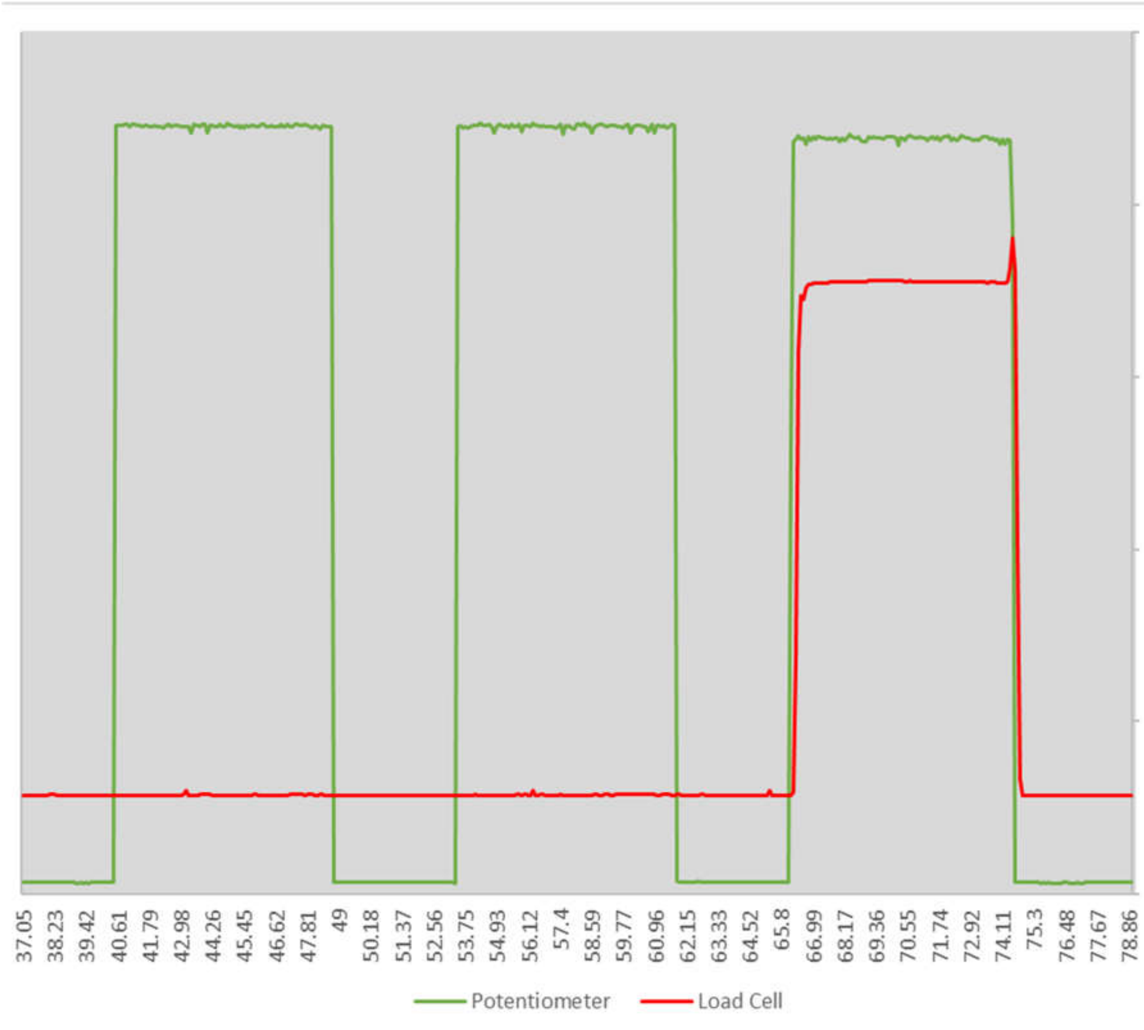

Figure 3.14: Detection of Empty Grip

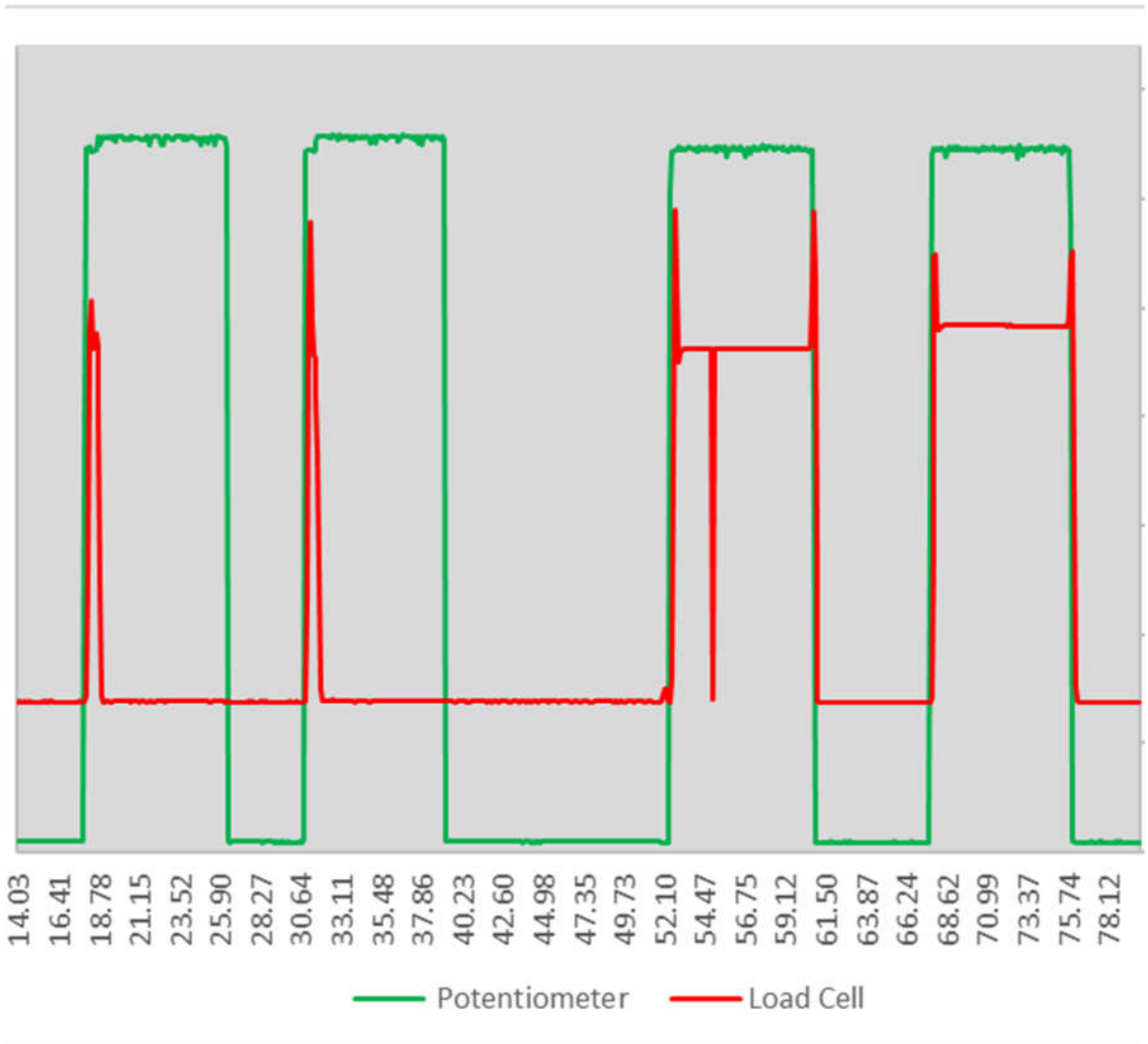

Figure 3.15: Detection of Slip in the Grip

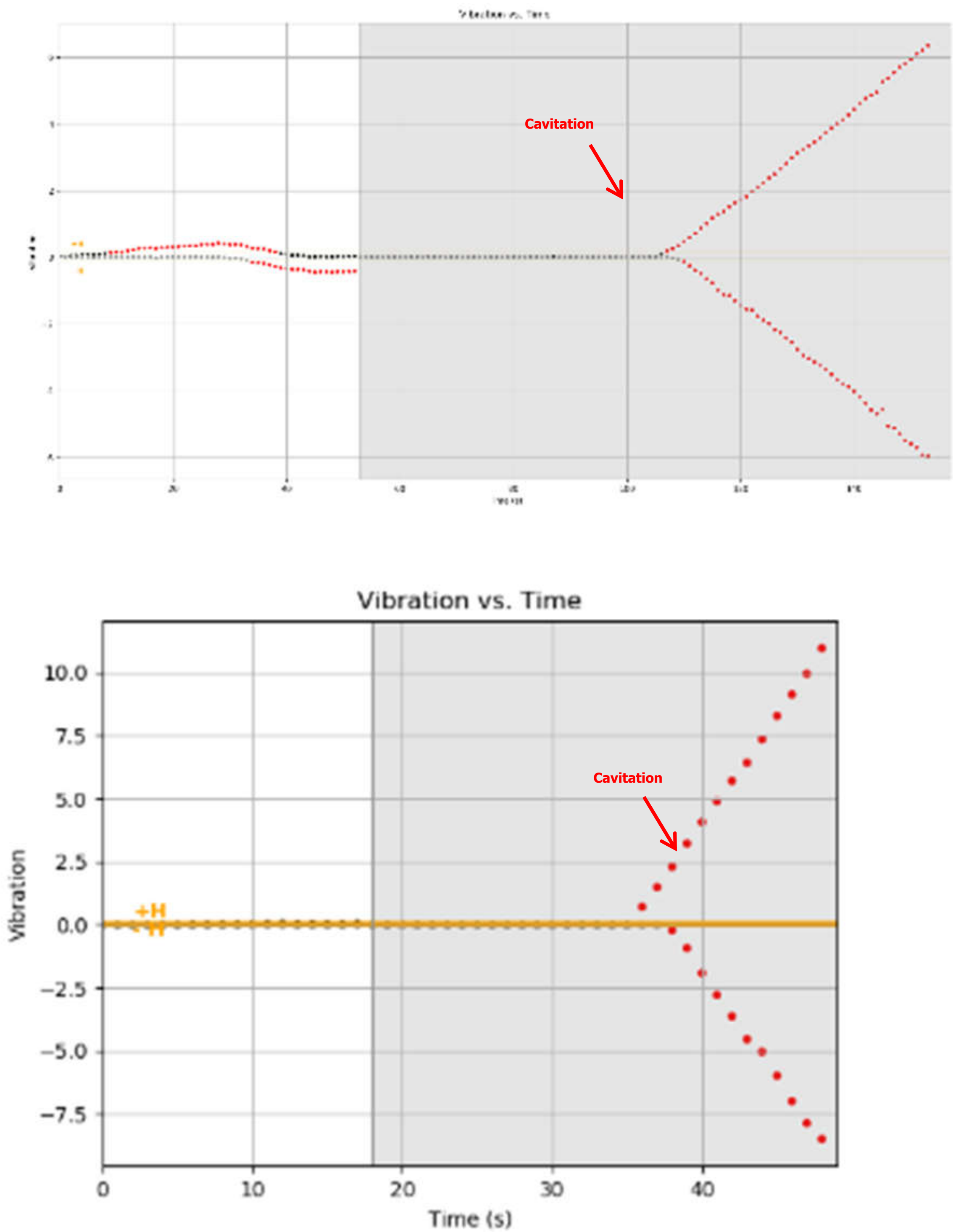

Figure 3.16: Cavitation Detection. (a) Motor DE, (b) Casing

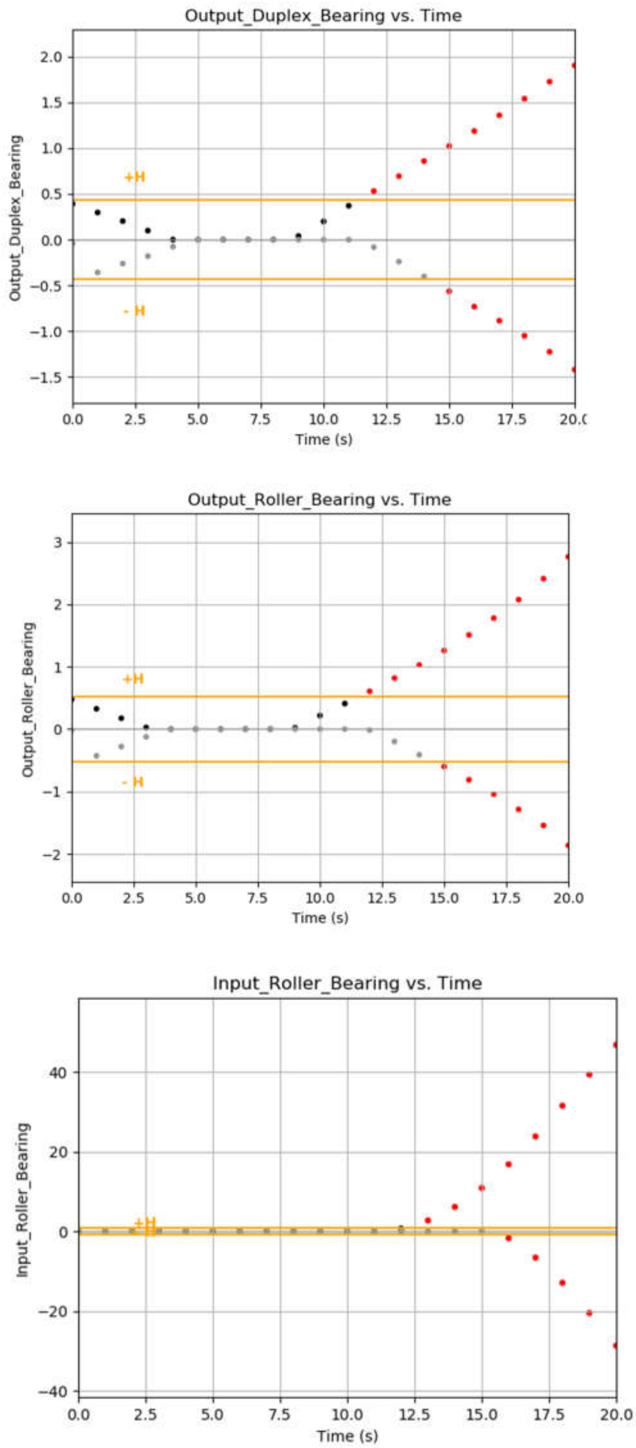

Figure 3.17: Gearbox fault detection. (a) Output Duplex Bearing. (b) Output Roller Bearing. (c) Input Roller Bearing

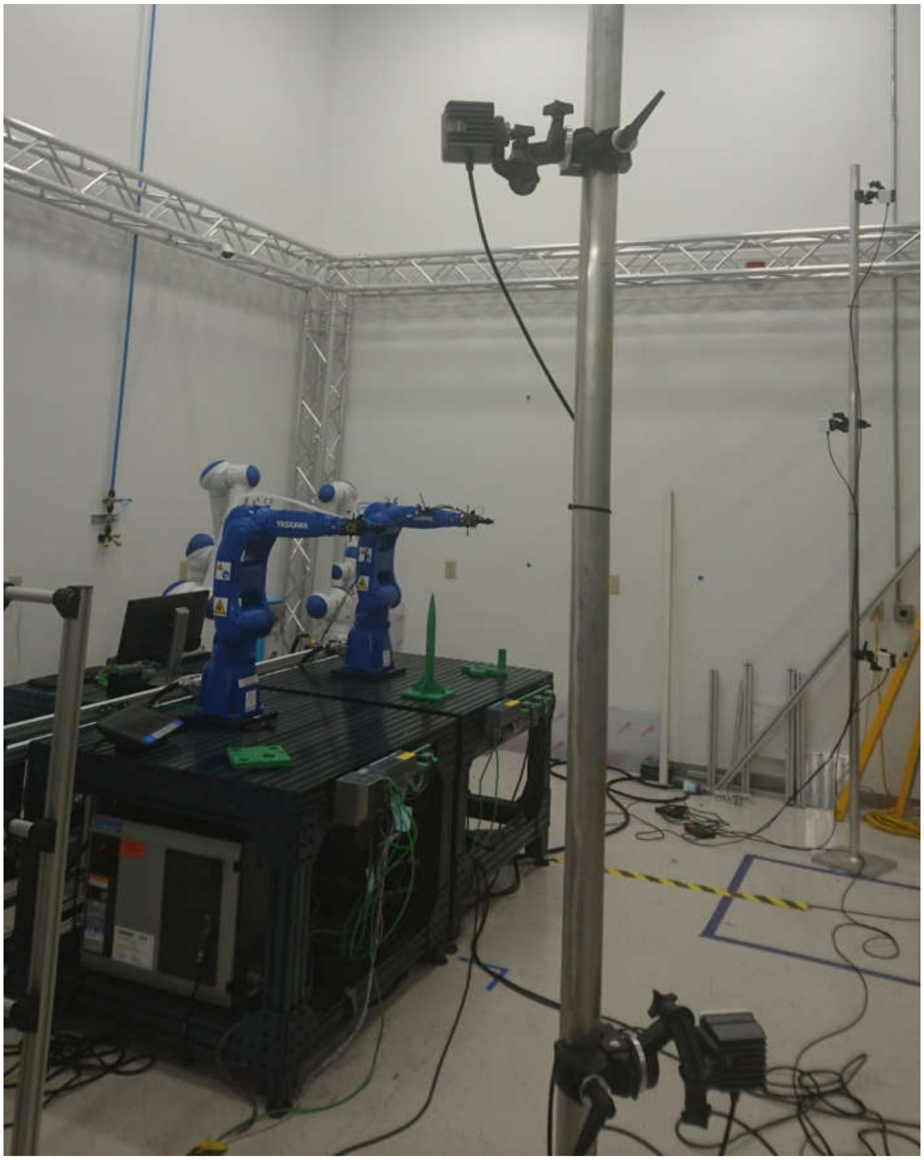

Figure 3.18: 2 poles with Motion Capture Cameras mounted

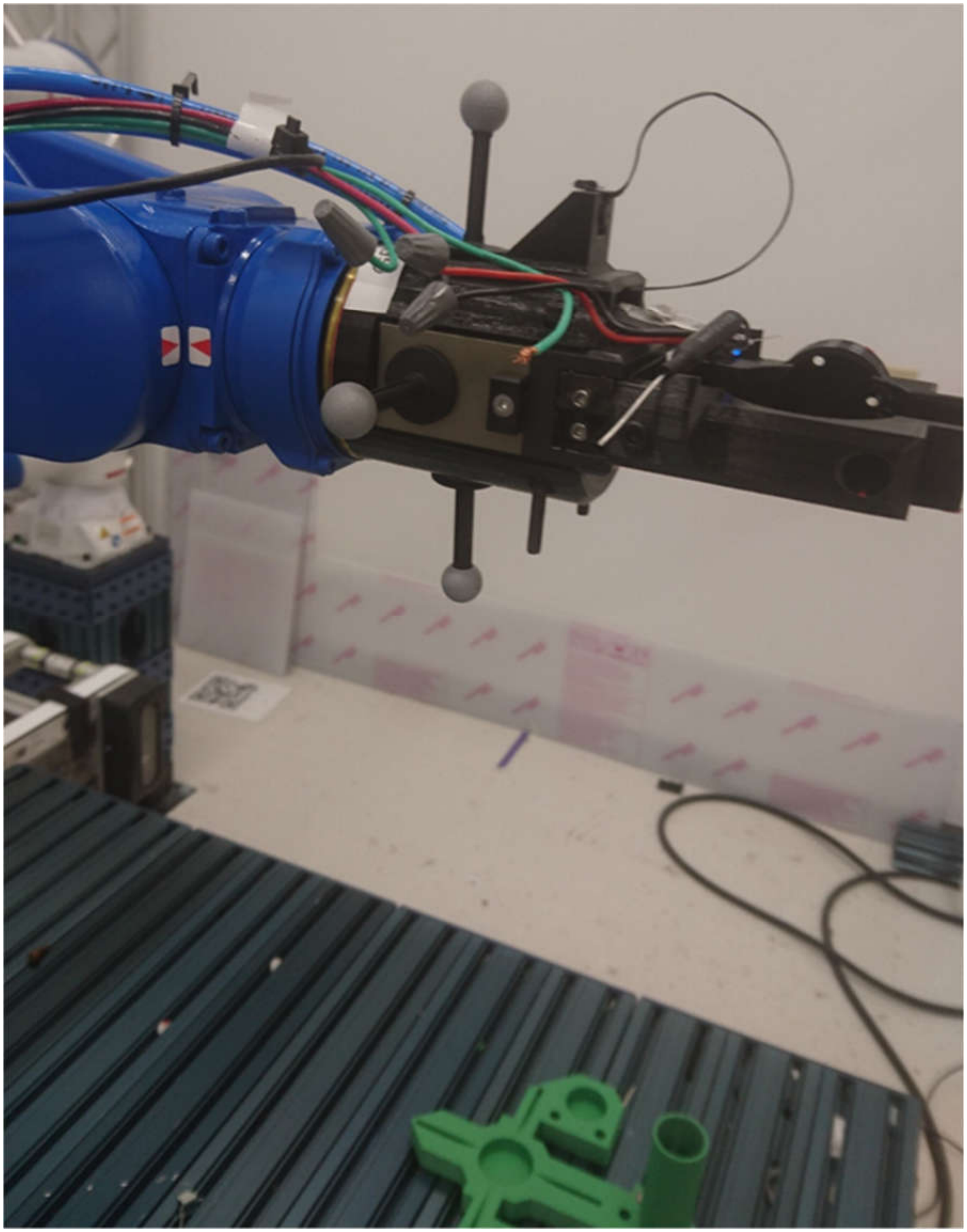

Figure 3.19: GP8 with motion capture balls attached to gripper

Figure 3.20: Calibration wand (left) and Calibration Triangle (right)

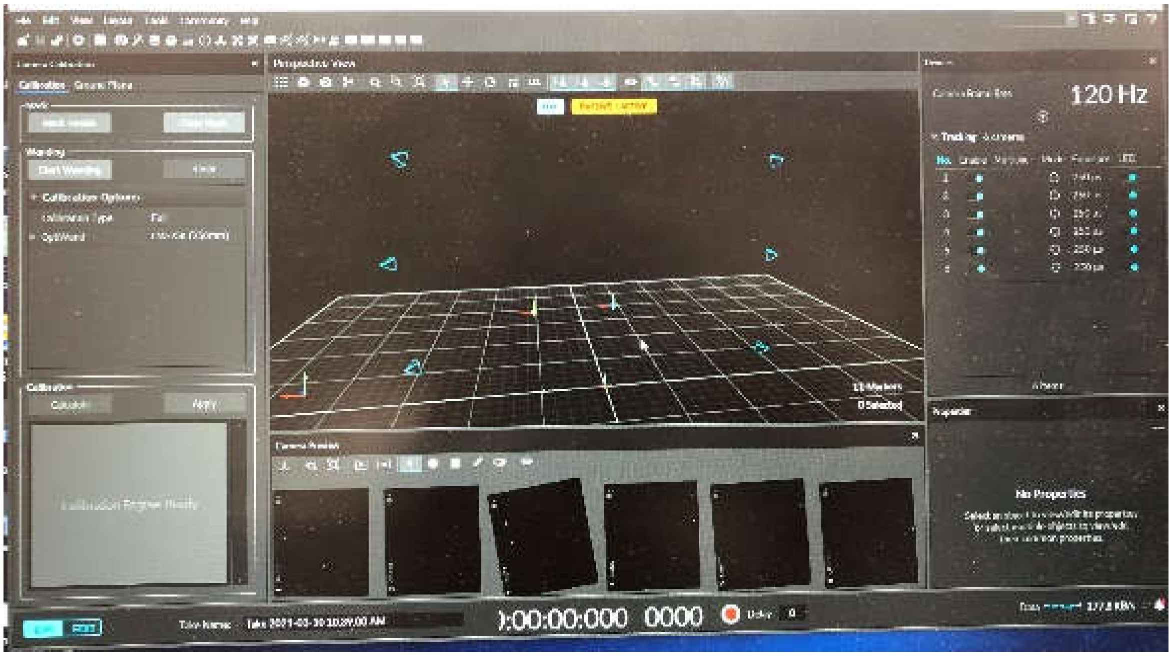

Figure 3.21: Visual representation of capture area within Motive

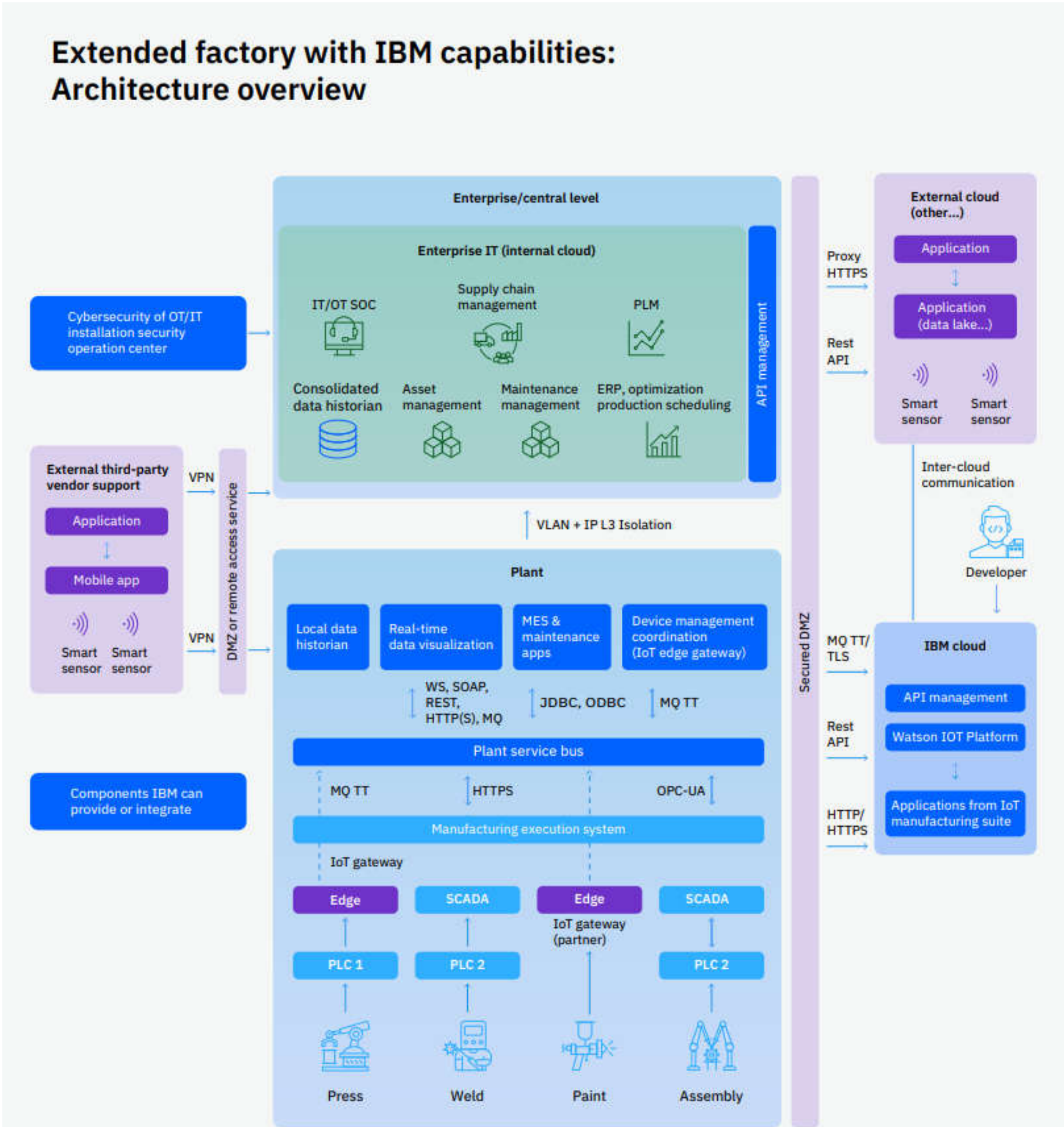

Figure 3.22: IBM I4.0 cloud-enabled smart manufacturing architecture [45]

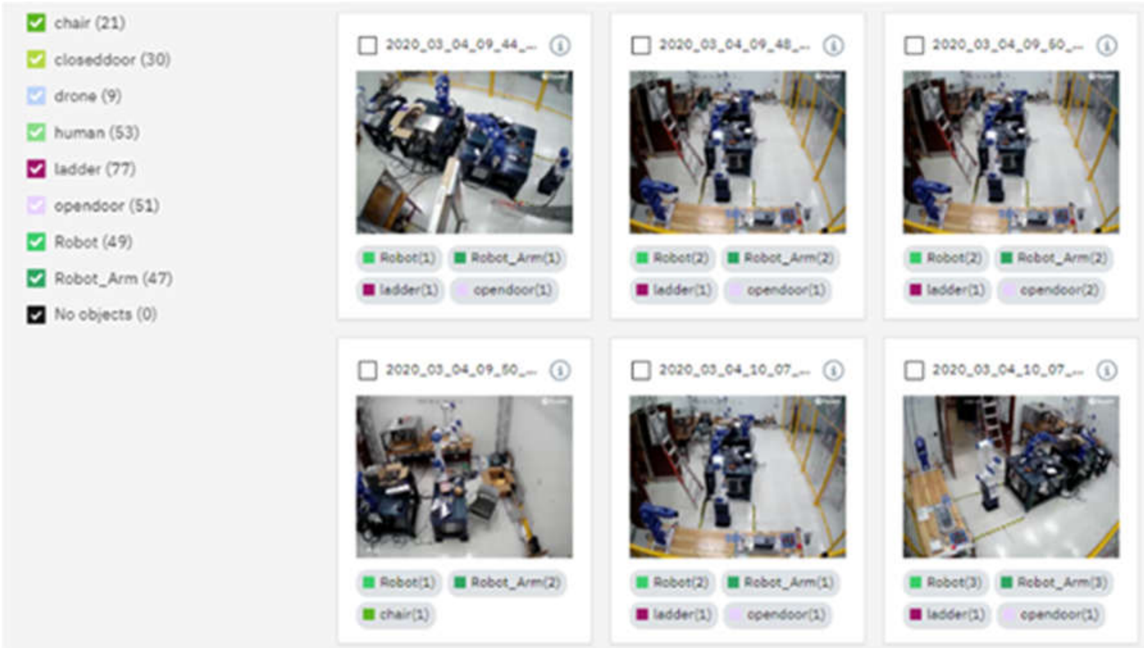

Figure 3.23: Define object classes for detection in Watson Studio™

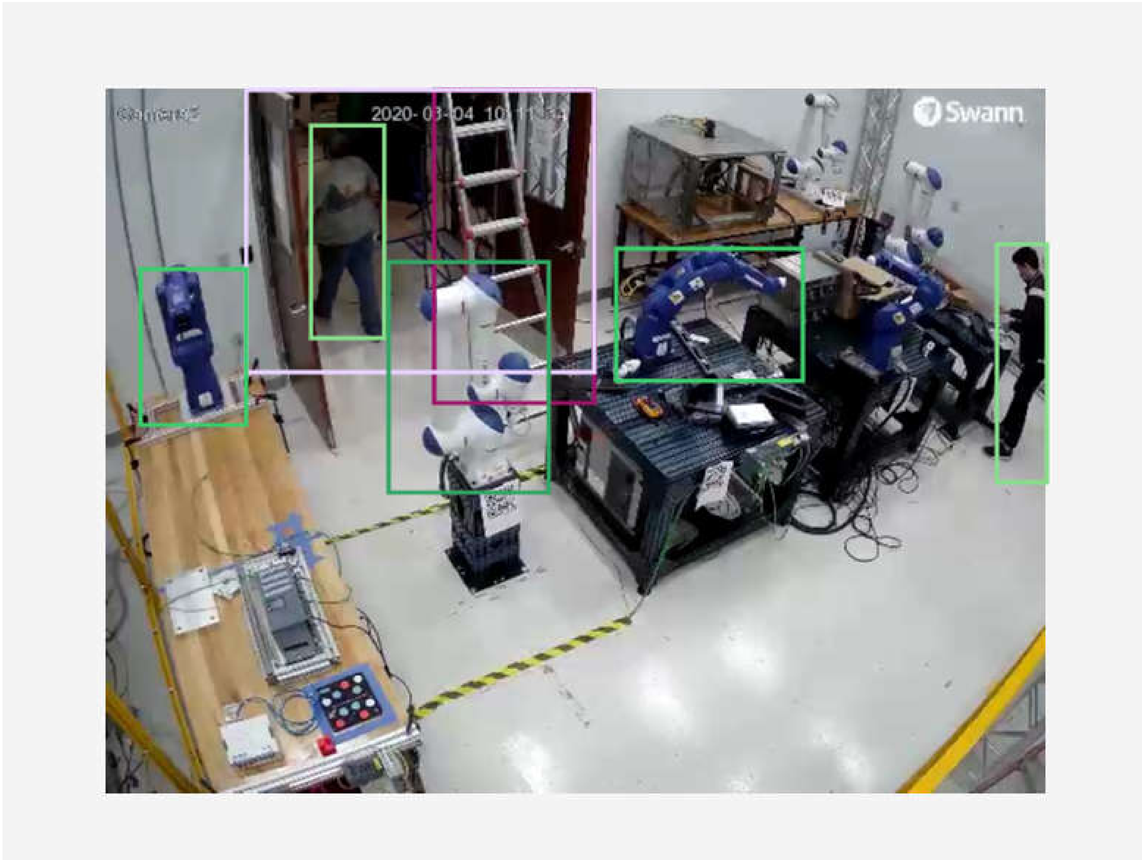

Figure 3.24: Region annotation by bounding boxes in Watson Studio™

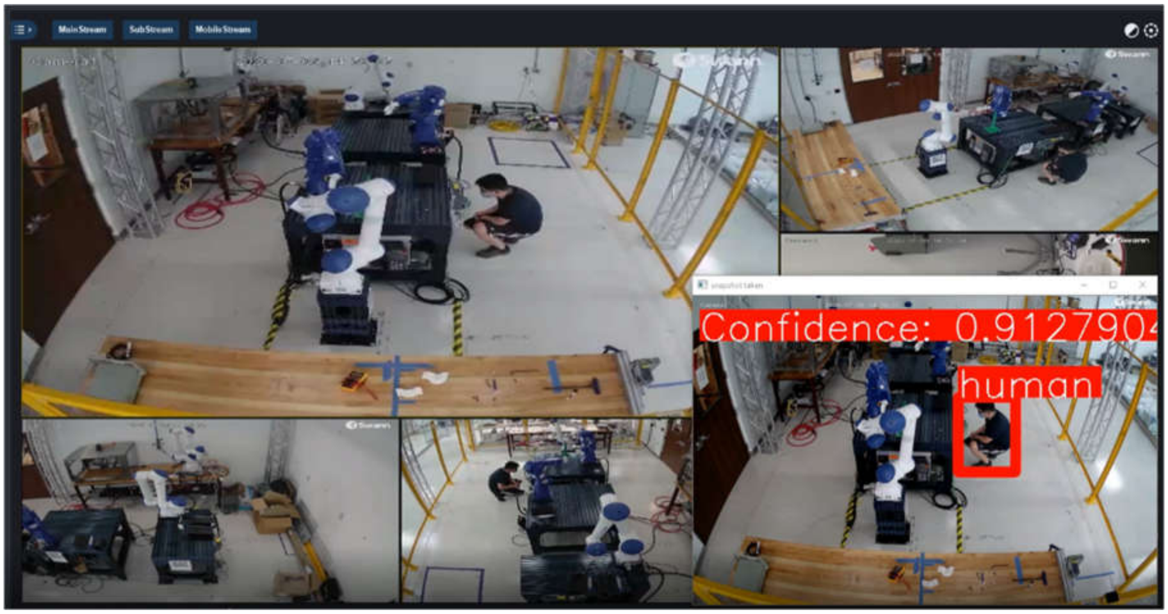

Figure 3.25: Integrating visual recognition into the cell for an alien object detection task

CHAPTER 4

CONCLUSION AND FINAL REMARKS

4.1 CONCLUSION

In this work, a novel approach is proposed to utilize digital transformation simulation and communication technologies to create virtual counterparts of robot manufacturing systems, on which the embedding of Big Data techniques into commonly used industrial robots, PLC function blocks, and event-driven controls at run-time is realized by this work. In addition, successful system integration of the robotic cell facilitates a general architecture of semantic-aware M2M communications by adding subsystems as communication layers.

The contribution of this work is primarily in the following aspects: (1) High-fidelity Virtual Commissioning platforms created by Siemens Tecnomatix Process Simulate are used as virtual environments to accommodate the model implementation, where system components are defined, simulated, and synchronized with live signals. After this offline programming process, generated robot programs can be directly transferred to physical robot systems without intermediate translations. (2) After construction of the virtual environment, system communications are implemented on both virtual and physical pathways.

“Software-in-the-loop” and “Hardware-in-the-loop” testing methods are discussed to be the baseline of virtual commissioning control loops depending on either the virtual cell is controlled by virtual or physical controller. Then, an application to enable IIoT for remote human intervention via customized OPC clients is presented. (3) An industrial virtual commissioning platform greatly augments the power of data analytics by interfacing through sensors and actuators with industrial simulation and automation software.

4.2 FUTURE WORK

The future work will focus on applying this methodology on more diverse manufacturing tasks and material flows, including collaborative assembly jobs, visual inspection, optimized rework, and continuous movement tasks. Dynamic feedback signals and high-dimensional manufacturing data will be automatically fed into the model to train, such as analog plant signals, product part CAD feature information, and machine vision inputs. Sensor signals from force sensors, motor voltages, robot monitors, thermal cameras, and environmental condition monitoring sensors will be used to connect to such systems so that more accurate real-time plant descriptions can be collected digitally. These manufacturing knowledges can also be shared between stakeholders with the proposed IIoT platform for even smarter decision-makings. Such attempts have the potential to enhance the use digital transformation technologies and approaches towards fully automated smart manufacturing systems, and delivering manufacturing intelligence driven by data from systems, processes.

4.3 SITUATION RESEARCH

The study of multimodal robotic health through IIoT, data analytics, and virtual commissioning represents an overall goal of Future Factories research undertaken at the University of South Carolina's McNair Center in the neXt Future Factories laboratory. This research complements a wide array of research topics covering different points of view in this field. These other areas of research attempt to (1) better understand and recognize mechanical features [37] and linking it to manufacturability analysis for additive manufacturing [120], (2) use machine learning for robotic inspection [101] and for feature recognition [119], (3) create digital twin driven manufacturing plants [134] and smart robotic assembly platforms [106], (4) create a comprehensive CPS product lifecycle environment [98] [66] while better understanding part criticality in inventory management [103] through better supplier risk assessment techniques [104][102].

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